Micro-data in Macroeconomics

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ABSTRACT

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This dissertation contains three essays on Macroeconomics. Detailed micro-level data is used in all three essays. The first chapter studies wealth inequality problems. More specifically, it focuses on capital return inequality among university endowments. It combines university-level data on endowment size, capital returns, and portfolio allocations into a unified dataset. Using panel data regression, I show a strong impact of size on investment return. Everything else the same, the biggest endowment has a capital return 8 percent higher than the smallest endowment. However, after adjusting for risk using Sharpe ratios, the strong positive correlation turns negligible or even negative. This result suggests that the higher return of bigger endowments can be attributed to risk compensation rather than to an informational premium.

The second and the third chapters employ firm-level data to study macroeconomic productivity. The second chapter documents the sectoral growth paths of measured total factor productivity (TFP) in southern Europe during the boom that proceeded the great contraction (1996 to 2007). Using both aggregate and firm-level panel data, I show that TFP in sectors that displayed fast expansion, such as construction, dropped significantly, while in non-expanding sectors, such as manufacturing, it stayed stable. I evaluate the relevance of two alternative explanations of this phenomenon: capital misallocation (the increase in capital was directed to less productive firms) and labor quality mismeasurement (lower quality of

incoming labor was not fully captured in the TFP calculation). I find that the misallocation channel is almost negligible. Moreover, worker-firm matched data shows that labor quality did deteriorate in the expanding sectors but not in the others, giving credence to the labor-quality mismeasurement hypothesis. A model featuring both the misallocation and the mismeasurement channels and calibrated to match the micro-level productivity distribution and labor quality distribution predicts that the drop in true TFP was small if labor quality is measured properly.

The third chapter documents the total factor productivity growth path in China from 1998 to 2015 using both the aggregate and the firm-level data. We find that measured TFP growth is positive from 1998 to 2011, before turning flat and even negative. A careful comparison between state-owned enterprises (SOEs) and private firms reveals that the slowing down of TFP growth of SOEs is the major contributor to the TFP growth reversal of the whole manufacturing sector. The reversal is not due to changes in the composition of production in different sub-sectors, but mostly due to changes within existing firms.

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For Yiyi Luo and Florent Qian Chen who make my productivity cyclical

Chapter 1

Do the Rich Know Better? – Evidence from University Endowments

1.1 Introduction

Capital return inequality (i.e., capital of bigger size has a higher return) is an accelerating force of the capital income inequality and thus worsens the wealth inequality. However, there exists very limited literature on this topic, and even fewer papers exploring the reasons for the situation due to the lack of data. Therefore, the question naturally arises, how serious is the capital return inequality? If it is, why does bigger capital outperform smaller capital?

Based on the data of university endowments in North America, this paper observes that the biggest university endowments exceed the smallest ones by 8 percent in terms of capital return. This can be explained by the hypothesis that bigger university endowments have more information about the financial market (the information channel), or that they just invest more proportionally in risky assets and thus on average achieve a higher capital return (the risk channel). The university endowment data dictates that the risk channel is the main contributor to the performance of the university endowments, while the information channel has a negligible impact. More specifically, after controlling for the risk using Sharpe ratios, bigger university endowments no longer reflect superior performance. Even after explicitly introducing the information channel, the risk channel still dominates.

Thanks to its unique structure and detailed data, National Association of College and University Business Officers (NACUBO) data enables me to investigate the severity of capital return inequality and to make distinctions between the information channel and the risk channel. It is a panel data set consisting of three pieces of material from 2000 to 2013: sizes,[1] capital returns,[2] and portfolio allocations. By regressing the capital returns on the sizes, I can quantify the capital return inequality. The panel data structure helps to introduce the university fixed effect, which can be considered as a control for unobserved variables, such as the reputation effect or network effect of universities. The panel regression result shows that if we keep the same fixed effect and only vary the sizes, then the biggest endowment is predicted to have a capital return rate 8 percent higher than the smallest one. To explain this huge capital return inequality, I follow NACUBO and Commonfund 2013 and link the eleven categories of assets in the portfolio allocations to benchmark indexes of the financial market. Then the weighted variance of the portfolio captures the risk channel, which can be used to compute the risk-adjusted performance: the Sharpe ratio. Furthermore, the absolute value of the difference between the actual return and the weighted portfolio return can serve as a proxy for the information channel. The assumption is that if an endowment with only public information invests exactly in the benchmark indexes, then the weighted portfolio return should be the same as the actual return. Hence the deviation of

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[1] The size is measured by the market capitalization of the endowment.

[2] The capital return is the total net rate of return on investment, where *total* means the inclusion of asset appreciation and *net* means the exclusion of management fees.

the latter from the former implies how much private information an endowment possesses. The panel regression of the Sharp ratios on the sizes gives a non-significant negative coefficient. And adding the information channel into the regression does not change the result. This demonstrates that the risk channel is the dominant channel.

Why does this paper focus on the institutional investors rather than the households as the primary concern of the capital return inequality is on the latter? It is because NACUBO has a panel data feature and more detailed categorizations of financial assets in comparison to available household data, such as that from the Survey of Consumer Finance (SCF). Although the SCF is a high-quality survey,[3] it cannot proper panel data because of the randomization of the household selection (Bricker and Sabelhaus 2015). Therefore, it is not possible to use the SCF data to identify the change in capital return for household i across two consecutive observations. For a university endowment in the NACOBO data, however, capital return history is well documented, which helps to introduce the university fixed effect and control for the heterogeneity besides the size of capital. Moreover, the eleven explicit categories for assets in NACUBO exhaust all the possible financial asset holdings of the university endowments, while “it is not possible, in general, to make direct separate estimates of the financial characteristics of the individuals in the survey households...” (CodebookSCF 2014).

There are other papers that also draw inferences about inequality from institutional investors. Piketty 2014 also uses NACUBO data to explain how capital income inequality

[3]While this is a generally held belief, there are papers that express doubts about the accuracy of the SCF, such as the work of Johnson and Moore 2008.

is aggravated by the capital return inequality and why. Without using the extensive micro-level data, Piketty compares the capital returns of three university endowments (Harvard, Yale, and Princeton) to that of the average university endowment in North America. He reaches the same conclusion that capital return inequality is severe. But the limitation of the data prevents him from further investigating quantitatively how much impact the size has on capital return, which is what this paper does. Nevertheless, he hypothesizes that the endowments of those elite universities have a higher capital return simply because they have the money to hire the best management teams and thus know more about the market. In other words, he argues that larger university endowments possess an informational advantage relative to smaller ones. The online appendix of Saez and Zucman 2016 includes the data on private foundations obtained from the IRS tax form PF-990. It demonstrates the same pattern of bigger private foundations outperforming the smaller ones on average.[4]

This article is linked to four strands of literature. First, the findings contribute to the literature on capital return inequality, which is still an under-explored subject compared to other inequality problems, such as income inequality and wealth inequality. A recent paper by Fagereng et al. 2016 employs the Norwegian administrative data, in which one can observe both the capital income and wealth holdings of households. They find that the positive correlation between the capital return and size can explain the gap between the actual wealth and imputed wealth through the capitalization method. My paper not only shows more direct evidence of the capital return inequality, but also goes a step further by identifying the channel behind it.

[4] It is included in the Table C14: Foundation real returns by wealth class, 1986-2010.

Second, the capital return inequality sheds some doubts on the capitalization method used in Saez and Zucman 2016, where the key assumption is that the capital return is homogeneous across the wealth distribution. The fact that bigger capital earns a higher return will cause a upward bias of the imputed wealth inequality by capitalization method. This is confirmed by Fagereng et al. 2016 that the imputed wealth has a much higher Gini coefficient than actual wealth. But it needs more research on since there are two important differences between Saez and Zucman 2016 and mine. First, the IRS tax data only captures realized capital income, while the capital return in the NACUBO data is the total return including unrealized capital gain for which no tax is paid. It might be true that bigger capital has a lot of unrealized capital gain. In addition, the observed IRS categorization of financial assets is very coarse compared to that of NACUBO: The former basically divides financial assets into fixed incomes and equities, while NACUBO divides assets into eleven categories.

Third, this article engages in the discussion of why capital return varies across investors and favors the risk channel instead of the information channel. Fama 1971 and Eugene F. Fama 1973 show both theoretically and empirically that riskier assets have a higher expected return on average, and that the financial market is efficient in the sense that price fully reveals information. Thus, the information channel should not play a role in capital return inequality. Yitzhaki 1987 explains the fact that larger investors invest proportionally more wealth in riskier assets due their lower relative risk aversion, while Gomes and Michaelides 2005 attribute it to the fixed cost of risky assets. However, Arrow 1987 argues with a simple model that large investors tend to purchase more private information because information is less costly for them than their smaller counterparts when it comes to comparing wealth. Thus, they know better about the market and enjoy a higher rate of return. More recent works, such as those by Piketty 2014 and Kacperczyk, Nosal, and Stevens 2014 share the same idea.

Fourth, the capital return inequality enriches the findings of the return to scale of mutual funds. Joseph Chen 2004 shows that the return declines with mutual fund size, which can be explained by the interaction of liquidity and organizational diseconomies. However, Reuter and Zitzewitz 2010 and Pastor, Stambaugh, and Taylor 2015 find that size has no impact on mutual fund performance using the regression discontinuity and the panel regression with fixed effect respectively. The difference of mutual funds and endowment funds may come from the fact that a mutual fund is much bigger in size on average than university endowments on average. The mean asset size in ibid. is $1,564 million, while that of NACUBO is only $440 million.

The rest of the paper is organized as follows: Section 1.1 discusses the data source and the merging strategy; Section 1.2 demonstrates the existence of capital return inequality; Section 1.3 then proves that the higher capital return of larger capital is mainly driven by taking more risk rather than by having more information; Section 1.4 shows other evidence as a robustness check; and Section 1.5 concludes the paper.

1.2 The Data

The paper's data comes from the National Association of College and University Business Officers (NACUBO). It is in panel data format, spanning across the year 2000 to 2013. The entity of the observation is in university endowment levels. The data consists of three pieces of information: the size of endowments measured in market value, the total net returns on investment, and the portfolio allocation weights. (Hereafter, I will refer to them respectively as the endowment size data, the capital return data, and portfolio allocation weights, and altogether as the endowment data, the NACUBO data or the NACUBO endowment data.) The total net return on investment is used interchangeably with the capital return in this paper. *Total* means that the return includes both realized and unrealized capital gain. And *net* means that the management fee is excluded from the return. This endowment data is collected annually by NACUBO based on the self-reporting files of endowments.

Before data analysis, the NACUBO data is needed to be unified.[5] One inconvenient feature of the NACUBO endowment data is that there is no other universal identifier except for the names of the university endowments.

However, the names are not strictly consistent. Roughly, there are three types of inconsistencies. 1. Abbreviation: For example, the State University of New York is sometimes recorded as SUNY. 2. University name changes: For example, before 2012, Mercyhurst University was called Mercyhurst College. 3. Prefix or suffix problems: For example,

[5] Although NACUBO has unified the annual capital return data in one Excel sheet, the other two pieces of data remain separated by year. Therefore I merge the endowment size data and the portfolio allocation data for each year with the capital return data, resulting in twenty-eight merges.

Dartmouth College is sometimes recorded as Trustees of Dartmouth College. If we use the traditional way of matching observations, we would not get a satisfactory result. Here I employ the fuzzy merge command "reclink" in Stata to match a large part of the endowments. Then I check manually to see if there are any incorrect matches and make the necessary corrections.

Table 1.1 and Table 1.2 show the general statistics of the NACOBO data. The number of the observations increases for all three pieces of data. This trend is a result of NACUBO's survey strategy. Once an endowment participates in the survey, it will get a reminder the following year to take part agin.[6] The incentive for the endowments to participate in the survey is the benefit that they can access the data set for research and comparison. The accuracy of the data is very good. Since most of the annual reports of endowments are publicly available, it is easy to cross check the figures in the NACUBO endowment data against those of the reports for any given endowment. Moreover, the number of observations is not exactly the same for all three pieces of data. The capital return data has fewer observations than the endowment size data and the portfolio allocation data.

There is a noticeable decrease in the observations in the endowment size data and portfolio allocation data from year 2009 to 2010. This gives rise to the concern of an attrition problem caused by endowment bankruptcy during or after the great recession. But it is not a real problem. First, although we do not have the data for the university bankruptcy rate, we know it is a rare event. Second, even though we attribute all the attritions to university bankruptcy, it does not bias the results very much. Table 1.3 shows the number of endow-

[6] A first-time participant can complete the survey on the NACUBO website.

Table 1.1: Statistics of Total Net Return and Endowment Size

	Total Net Return					Endowment Size ($)				
year	N	mean	sd	min	max	N	mean	sd	min	max
2000	450.0	13.5	13.3	-12.2	183.0	545.0	4.4e+08	1.3e+09	968000.0	1.9e+10
2001	554.0	-3.5	6.3	-32.9	24.8	588.0	4.0e+08	1.2e+09	1145000.0	1.8e+10
2002	591.0	-6.2	4.5	-27.0	10.1	666.0	3.3e+08	1.1e+09	159000.0	1.7e+10
2003	626.0	3.2	3.1	-10.2	31.0	684.0	3.4e+08	1.1e+09	321000.0	1.9e+10
2004	646.0	15.3	4.0	-1.0	25.4	707.0	3.8e+08	1.3e+09	370000.0	2.2e+10
2005	662.0	9.4	3.3	-11.0	22.3	710.0	4.2e+08	1.5e+09	4738.0	2.5e+10
2006	684.0	10.8	3.5	-2.7	23.0	731.0	4.6e+08	1.7e+09	488000.0	2.9e+10
2007	697.0	17.3	3.8	2.1	62.2	749.0	5.4e+08	2.0e+09	571000.0	3.5e+10
2008	700.0	-2.9	4.1	-22.6	12.1	761.0	5.4e+08	2.1e+09	596000.0	3.7e+10
2009	748.0	-18.6	5.6	-40.0	23.3	823.0	3.8e+08	1.5e+09	597677.0	2.6e+10
2010	759.0	11.9	3.4	-18.3	36.2	795.0	4.1e+08	1.6e+09	747048.0	2.8e+10
2011	753.0	19.2	4.3	-4.2	31.8	789.0	5.0e+08	1.9e+09	574049.0	3.2e+10
2012	741.0	-0.3	2.7	-9.5	15.8	766.0	5.1e+08	1.9e+09	609747.0	3.0e+10
2013	788.0	11.8	2.5	1.2	27.6	809.0	5.4e+08	2.0e+09	713687.0	3.2e+10
Total	9399.0	5.8	11.7	-40.0	183.0	10123.0	4.4e+08	1.7e+09	4738.0	3.7e+10

Total Net Return means that the return rate of the endowment investment includes capital appreciation and excludes management fees.
Endowment size is measured in terms of the market value of endowment assets.
NACUBO Endowment-level Data

Table 1.2: Portfolio Allocation Mean (percent)

year	N	DE	FI	EQI	PE	ALT	VC	RE	EN	COM	DD	CASH	OTHER
2000	528.0	50.7	23.1	11.4	0.9	2.7	2.4	2.1	0.3	0.1	0.3	4.2	1.8
2001	585.0	49.9	24.8	9.6	0.9	3.4	1.5	2.4	0.3	0.0	0.3	4.1	2.3
2002	629.0	46.3	26.2	9.8	1.1	5.0	0.9	2.6	0.4	0.0	0.0	3.9	1.5
2003	669.0	47.6	25.6	9.7	1.4	6.2	0.8	2.8	0.4	0.0	0.0	4.0	1.5
2004	695.0	49.1	21.9	11.0	1.4	7.4	0.8	2.7	0.6	0.0	0.0	3.7	1.4
2005	699.0	45.7	21.4	12.8	1.6	8.8	0.9	3.1	1.0	0.0	0.0	3.5	1.3
2006	717.0	42.5	19.9	15.3	2.0	9.6	0.9	3.5	1.5	0.0	0.0	3.4	1.3
2007	722.0	40.5	18.3	17.1	2.3	10.8	1.0	3.5	1.6	0.0	0.0	3.5	1.3
2008	717.0	35.0	19.1	17.0	3.4	12.9	1.1	4.2	2.3	0.0	0.0	3.6	1.4
2009	836.0	33.6	21.7	14.3	3.3	13.1	1.2	2.3	1.6	0.7	0.9	5.6	1.7
2010	775.0	32.5	21.7	14.7	3.8	13.9	1.1	1.9	1.9	1.0	1.1	4.1	2.0
2011	793.0	32.4	18.9	16.5	4.2	14.2	1.3	2.2	2.2	1.3	1.0	3.9	1.9
2012	764.0	31.2	19.7	15.4	4.5	14.7	1.5	2.6	2.3	1.5	1.1	3.6	1.9
2013	810.0	32.4	17.7	17.0	4.2	12.5	1.3	2.5	2.4	1.3	0.8	6.1	1.9
Total	9939.0	39.9	21.2	13.9	2.6	10.1	1.2	2.7	1.4	0.5	0.4	4.1	1.6

Domestic Equities(DE), Fixed Income(FI), International Equities(EQI), Private Equity(PE), Marketable Alternatives(ALT), Venture Capital(VC), Real Estate(RE), Energy and Natural Resources(EN), Commodities(COM), Distressed Debt(DD), Short-Term Securities/Cash(CASH)
NACUBO Endowment-level Data

ments that appear in the data set in year t but disappear in year $t+1$ and $t+2$.[7] Generally, the attrition problem is not very severe since the attrition percentage is rarely above 5 percent.[8]. We do see that the attrition problem is slightly more severe in year 2009. However, the attrition is not concentrated only in one group. In face, 2.55 percent attrition comes from the endowments smaller than \$10 million, 4.5 percent from endowments smaller than \$1 billion and larger than \$10 million, and 0.4 percent from the biggest group.

Table 1.3: Attrition Problem of Endowment Data

	Endowment Size			**Portfolio Allocation**		
year	**N**	**# Attr.**	**% Attr.**	**N**	**# Attr.**	**% Attr.**
2000	545	11	2.0	528	16	3.0
2001	588	38	6.5	585	21	3.6
2002	666	3	0.5	629	25	4.0
2003	684	27	3.9	669	28	4.2
2004	707	29	4.1	695	34	4.9
2005	710	15	2.1	699	24	3.4
2006	731	27	3.7	717	37	5.2
2007	749	19	2.5	722	26	3.6
2008	761	44	5.8	717	49	6.8
2009	823	71	8.6	836	73	8.7
2010	795	28	3.5	775	22	2.8
2011	789	26	3.3	793	51	6.4
2012	766	39	5.0	764	10	1.3

Definition of attrition in year t: Observed in year t, but not observed in year $t+1$ and $t+2$.
NACUBO Endowment-level Data

[7] For year 2012, we just count the number of endowments that appear in the data set in year 2012 and then disappear in year 2013.

[8] This attrition percentage can be seen as the upper bound of the endowment bankruptcy since endowments also drop out of the data set for other reasons.

1.3 Quantifying Capital Return Inequality

In this section, I prove that the capital return inequality exists and is actually very severe by using the capital return data and the endowment size data.

Figure 1.1 shows the ten-year average annual nominal return for endowment groups with different sizes. This data is collected from NACUBO's annual reports, not calculated by university-level data. The history spans from 1988 to 2013, much longer than the unified data set.[9] This figure roughly proves the existence of the capital return inequality. There is a clear rank of capital return: Groups of bigger endowments are almost always above the groups of smaller ones. The differences of capital return between the largest endowment and the smallest ones are quite stable, varying between 2 percent and 4 percent.

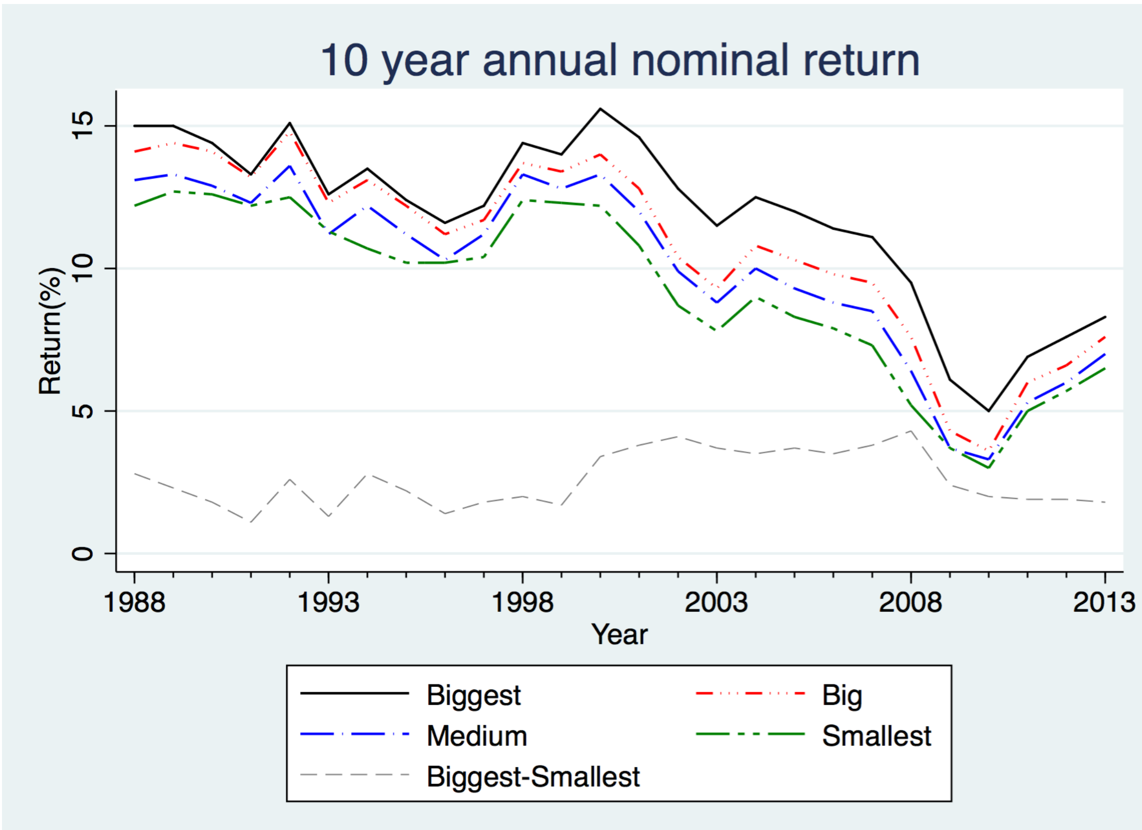
The next step is to quantify the capital return inequality more precisely. More specifically, I check whether an increase in endowment size results in an increase in capital return and by how much. To see this, I run the panel regression specified in equation 1.1:

$$RTN_{it} = \alpha_i + \beta_1 \ln ENDOW_{it} + \Sigma_{t=2000}^{2012} \delta_t year_t + \varepsilon_{it} \tag{1.1}$$

RTN_{it} is the total net investment return of endowment i in year t. α_i is the endowment fixed effect, which accounts for the unobserved variables, such as the reputation effect or the network effect of universities. The year dummy $year_t$ accounts for the macroeconomic variation, such as economic booms and recessions. $\ln ENDOW_{it}$ is the log value of en-

[9] I use the group return data from NACUBO's annual reports, not calculated from university-level data, even after 2000 is to maintain consistency. In actuality, the two are very similar.

Figure 1.1: Total Net Return of University Endowments of Different Sizes



Ten-year annual nominal return is calculated as the geometric mean of yearly nominal return over a moving window of ten years.

1988-1997: Smallest $25 million and under, medium $25 million - $100 million, big $100 million - $400 million, biggest over $ 400 million

1998-1999: Smallest $75 million and under, medium $75 million-$300 million, big $300 million - $1 billion, biggest over $ 1 billion

2000-2013: Smallest $100 million and under, medium $100 million - $500 million, big $500 million - $1 billion, biggest over $ 1 billion

From 2002 onwards, there are in total six categories, but I calculate the equally weighted mean of the lowest three categories to make the results comparable to 2000 and 2001

From NACUBO annual reports. It is only available on an aggregate level, not on the university-level.

dowment size. ε_{it} is the error term.

The parameter of interest is β_1. In order to solve the problem of serial correlation, the estimation employs White's heteroskedasticty-consistent estimator, following Arellano 1987. In the baseline specification column 1 of Table 1.4 , which is the panel regression with fixed effect, $\hat{\beta}_1 = 0.822$. The standard error is clustered by endowments, and the result is statistically significant at a level of 95 percent.

Table 1.4: Regression of Return on Endowment Size

	W/ FE	**W/O FE**	**W/O FE**	**2003 - 2013**	**2003-2013 EX. >1b**
	(1)	(2)	(3)	(4)	(5)
LENDOW	.822**	.513***		.955**	1.01**
L2.LENDOW			.428***		
S.E.	.361	.043	.039	.448	.492
R^2	.8351	.8367	.9046	.8935	.8913
Obs.	(970,8811)	8811	6670	(948,7162)	(908,6573)

In the row "Obs.", (970, 8811) means that the regression is run with fixed effect, 8811 is the total number of observations, and 970 is the number of groups.
Standard error is heteroscedasticity-consistent, and clustered by university endowment.
L2.LENDOW means the two periods lagged ln $ENDOW$.
Column (1) panel regression with fixed effect.
Column (2) panel regression without fixed effect.
Column (3) panel regression without fixed effect and the endowment size is lagged for two periods.
Column (4) panel regression with fixed effect using the subperiod from 2003 to 2013.
Column (5) panel regression with fixed effect using the subperiod from 2003 to 2013 and excluding endowments larger than $1 billion.
NACUBO Endowment-level Data

How should the severity of the capital return inequality be interpreted? Take one of the smallest endowments in 2013, Georgia Perimeter College, with an endowment size equal to $1.17 million, and enlarge its size to the level of Harvard University, which is $32.3 billion. The predicted capital return would increase by 8.4 percent. If we use the average capital return rate, 5.8 percent, in Table 1.1 for both endowments, the capital income difference is \$187.3 million. However, if we assume that Harvard University has a capital return that equals to $5.8\% + \frac{8.4\%}{2} = 10\%$,[10] and that Georgia Perimeter College $5.8\% - \frac{8.4\%}{2} = 1.6\%$,[11] the predicted capital income difference would be close to \$323 million, which by itself is almost three hundred times the size of the endowment of Georgia Perimeter College. Thus, the capital return inequality exacerbates the capital income inequality.

There are some concerns about equation 1.1. First, why do I use the regression with fixed effect as baseline specification instead of random effect? It is because the fixed effect can fix the omitted-variable bias. University endowments have different investment philosophies, reputation, network and management teams, etc. All these characteristics are potentially correlated with the size of the endowment. Thus, the regression without fixed effect could bias the estimation of coefficient β_1. Pastor, Stambaugh, and Taylor 2015 include the fixed effect using the same argument. Moreover, the Hausman test favors the fixed effect specification. Nevertheless, I include the result of the panel regression without fixed effect as well in estimation for equation 1.1. Although the coefficient of interest declined to $\hat{\beta}_1 = 0.513$ as in column 2 of Table 1.4, it does not change the qualitative result. The predicted capital return difference between Harvard University and Georgia Perimeter College is still 5.2 percent.

Another valid concern is that the significance of $\hat{\beta}_1$ may be due to some mechanical mechanism rather than any interesting economic explanation. It is true that a higher capi-

[10] The endowment of Harvard University had a capital return rate of 11.3 percent in year 2013.

[11] The endowment of Georgia Perimeter College had a capital return rate of 5.79 percent in year 2013.

tal income in year t results in a higher capital return and a bigger endowment size in year t when keeping everything else the same, including the endowment size in year $t-1$. However, this argument has amplified the role of investment income in determining the size of an endowment by ignoring the expenditure or other sources of the variation of the size. If we assume that the endowment of Yale University has accumulated all its capital income without consumption or any other variation in size from 2000 to 2013, its endowment should have been \$34 billion in 2013, even slightly bigger than the size Harvard University's endowment, which is \$32.3 billion at the same time. However, the actual size of Yale's endowment in 2013 was \$21 billion. Moreover, column 3 of Table 1.4 shows the result of panel regression with the lagged size variable ln $ENDOW_{it-2}$, where the coefficient $\hat{\beta}_1$ drops from 0.513 to 0.43, but still remains both economically and statistically significant. Even with $\hat{\beta}_1 = 0.43$, the predicted return increase would be about 4 percent if the size of Georgia Perimeter College's endowment becomes as big as Harvard's.

Third, the attrition problem may cause selection bias: In other words some endowments leaving the data set because of bankruptcy could give a biased estimation of β_1. However, as I have discussed in the previous section, attrition could hardly be a problem after the financial crisis of 2008, which is probably the period most prone to the issue. Even if attrition is a severe problem, as long as the endowments that disappeared from the data set were relatively small in size, the true β_1 could be even bigger than $\hat{\beta}_1$. Only when the bankrupt endowments are relatively large ones does my estimation have an upward bias.

As a robustness check, I also run the panel regression with fixed effect using subperiod and subsample. The results are reported in columns 4 and 5 of Table 1.4. The estimated $\hat{\beta}_1$

is even larger than the baseline specification.

To conclude, the existence of the capital return inequality is consistent with Piketty 2014's finding. Moreover, I can quantify that the capital return inequality is very severe.

1.4 Risk Channel vs. Information Channel

In this section, I show that the risk channel is the major reason for capital return inequality by using the portfolio allocation data.

Table 1.2 shows that the portfolio allocation data consists of eleven specified asset types and one unspecified asset type. They are respectively domestic equities, fixed income, international equities, private equity, marketable alternatives, venture capital, real estate, energy and natural resources, commodities, distressed debt, short-term securities and cash, and others. On average, university endowments invest most heavily in domestic equities and fixed income, which account for more than 60 percent together. But there is a clear trend suggesting the decreasing importance of these two assets. Moreover, the weight of international equities, private equity and marketable alternatives is increasing.

Synthetic Return

This subsection shows how to impute the synthetic return based on the portfolio allocation and publicly available benchmark indexes, and how it helps alleviate the concern over the missing data. The next subsection adds that the synthetic return can also be used to construct a proxy for the information channel.

According to NACUBO and Commonfund 2013, I assign eleven benchmark indexes to match asset types.[12] Table 1.5 shows the match between the asset types and the benchmark indexes. All the indexes are widely used and well accepted by the financial market. For example, the S&P 500 index serves as a proxy to the domestic equities, the Barclays US Aggregate index proxies the fixed incomes, and MSCI World ex-USA proxies the international equities.

Table 1.5: Assets and Benchmark Indexes Match

Asset Class	**Abbreviation**	**Benchmark Index**
Domestic Equities	DE	S&P 500
Fixed Income	FI	Barclays US Aggregate
International Equities	EQI	MSCI World ex-USA USD
Private Equity	PE	Commonfund Capital Private Equity
Marketable Alternatives	ALT	HFRI Fund of Funds
Venture Capital	VC	Commonfund Capital Venture Capital
Real Estate	RE	NCREIF Open-End Diversified Core
Energy & Natural Resources	EN	S&P Global Natural Resources
Commodities	COM	DJ-UBS Commodity
Distressed Debt	DD	HFRI Distressed Debt
Short-Term Securities/Cash	Cash	S&P/BGC 0-3m US T-bill TR

Details of the categorization: Standard & Poor's (S&P), Morgan Stanley Capital International (MSCI), Hedge Fund Research Indices(HFRI), National Council of Real Estate Investment Fiduciaries (NCREIF), Dow Jones (DJ), and BGCantor (BGC) (Following NACUBO 2013 Report).

[12] We do not assign any index to the unspecified asset type for two reasons: First, the weight of this asset is under 2 percent; Second the NACUBO data does not clearly define what *other* means.

Table 1.6 presents the annual returns of all assets, except for private equity and venture capital.[13] The benchmarks of these two assets are both from Commonfund, an institutional investment firm that delivers investment solutions for nonprofits organizations, including university endowments. Commonfund collaborates with NACOBU[14] but does not share their data with outsiders. Since different private equity and venture capital funds may have very different strategies, it would be inaccurate to use a random private equity or venture capital fund whose data is publicly available.

Table 1.6: Benchmark Indexes Annual Return

year	DE	FI	EQI	PE	ALT	VC	RE	EN	COM	DD	CASH
2000	13.3	11.6	5.5	.	19.6	.	14.3	.	31.8	10.5	6.1
2001	-26.8	8.4	-29.4	.	-0.8	.	5.6	.	-19.5	7.0	4.1
2002	-17.1	10.3	-14.2	.	2.1	.	5.5	.	25.9	2.5	1.7
2003	22.3	4.1	29.7	.	9.0	.	9.3	41.6	23.9	27.6	1.1
2004	13.1	4.3	22.1	.	5.7	.	13.1	24.4	9.1	17.3	1.3
2005	10.4	2.4	25.1	.	10.3	.	21.4	26.8	21.4	15.3	3.0
2006	10.6	4.3	20.5	.	7.0	.	16.3	29.8	2.1	11.3	4.8
2007	18.4	7.0	26.3	.	14.0	.	16.0	41.7	16.2	11.6	4.7
2008	-23.3	5.2	-29.0	.	-10.9	.	-10.0	-38.3	-35.6	-11.4	1.7
2009	-8.9	5.9	0.6	.	-1.2	.	-29.8	36.1	18.9	1.7	0.1
2010	13.6	6.5	7.1	.	3.5	.	16.4	11.0	16.8	13.1	0.1
2011	-2.2	7.8	-11.2	.	-1.8	.	16.0	-14.9	-13.3	0.4	0.0
2012	34.4	4.2	18.2	.	2.9	.	10.9	7.2	-1.1	8.5	0.1
2013	20.0	-2.0	21.4	.	6.5	.	13.9	1.5	-9.5	13.6	0.0
Mean	5.5	5.7	6.6	.	4.7	.	8.5	15.2	6.2	9.2	2.0

Domestic Equities(DE), Fixed Income(FI), International Equities(EQI), Private Equity(PE), Marketable Alternatives(ALT), Venture Capital(VC), Real Estate(RE), Energy and Natural Resources(EN), Commodities(COM), Distressed Debt(DD), Short-Term Securities/Cash(CASH)
From publicly available benchmark indexes

Synthetic return is calculated using equation 1.2, meaning that it is the weighted average

[13] But the raw data is in quarterly frequency.

[14] The NACUBO endowment reports are compiled by Commonfund.

of market returns.

$$RTN_{it}^{syn} = \Sigma_a R_{at} W_{it}^a, \tag{1.2}$$

where R_{at} is the return of benchmark index for asset a at time t, and W_{it}^a is the portfolio weight of asset a of endowment i at time t.

Table 1.7 compares actual return and synthetic return. Only the data of the subperiod from 2003 to 2013 is used. This is because 1) the benchmark data for energy and natural resources is missing from 2000 to 2002; and 2) the definition of portfolio allocation data is very different in years 2000 and 2001 from the rest of the years. Synthetic return is calculated in two ways: by treating the missing returns of private equity and venture capital as zero or replacing them with the return of index for commodities. The result in Table 1.7 demonstrates that the statistics of the synthetic return and the actual return are very similar. Moreover, if we replace the dependent variable RTN_{it} in equation 1.1 with RTN_{it}^{syn} and run the same regression, the coefficient $\hat{\beta}_1$ is very close. The upper panel of Table 1.7 shows this with all the endowments from 2003 to 2013. If we ignore the missing data of private equity and venture capital, and set them to zero, the coefficient $\hat{\beta}_1$ is 0.7, not far from the benchmark case where $\hat{\beta}_1$ is 0.955. And if we assign the return of commodities to private equity and venture capital, the coefficient increases slightly to 0.72.

The lower panel of Table 1.7 focuses on the endowments with a size below 1 billion dollars. The coefficient $\hat{\beta}_1$ with the synthetic return is even closer to that of the actual return, which is 1.01 in this specification. This result suggests that the similarity between

Table 1.7: Similarity between Actual Return and Synthetic Return

Var.	**Obs.(Reg.)**	**Mean**	**SD**	**Min**	**Max**	**Coef. β_1(se)**
Full Sample	**2003-2013**					
RTN	7804(7162)	6.93	11.32	-40	62.2	.955(.448)**
$RTN_{syn}(PE = VC = 0)$	8197(7162)	7.08	9.33	-30.66	30.45	.695(.260)***
$RTN_{syn}(PE = VC = COM)$	8197(7162)	7.13	9.81	-30.66	30.45	.722(.267)***
Exclude Endow $>$ 1b	**2003-2013**					
RTN	6772(6573)	6.65	11.44	-40	62.2	1.01(.492)**
$RTN_{syn}(PE = VC = 0)$	7400(6573)	7.13	9.33	-30.66	30.45	.839(.290)***
$RTN_{syn}(PE = VC = COM)$	7400(6573)	7.18	9.71	-30.66	30.45	.928(.297)***

The column "Obs. (Reg.)" means that the total number of observations of RTN is 7804, and 7162 observations enter into the regression using equation 1.1.
Standard error is heteroscedasticity-consistent, and clustered by university endowment.
NACUBO Endowment-level Data, and publicly available benchmark indexes

the synthetic return and the actual return is higher if we exclude the biggest endowments. One possible explanation is that bigger endowments deviate more from benchmark indexes than smaller ones.

The takeaway message of this subsection is that the missing returns of private equity and venture capital will not affect the result very much. This is due to the fact that the weights of private equity and venture capital in portfolio allocation are tiny. Although there is an upward trend for private equity, the weight has not surpassed 5 percent yet. The weight of venture capital is rarely above 2 percents, which is almost at the same level as the asset categorized as *others*.

Controlling for the Risk Channel

In this subsection, I explore whether the risk channel contributes to the capital return inequality. The risk of an endowment in investment activity is defined as the volatility of the portfolio, which is calculated by the weighted volatility of the excess return of benchmark indexes.

Risk-adjusted performance is used to check how important the risk channel is. The idea is that if the risk-adjusted performance of endowments is still positively correlated with the size, it means that besides the risk channel, the information channel also contributes to the higher return of larger endowments. However, if the positive correlation disappears after I replace the return with the risk-adjusted performance, then we can conclude that the risk channel dominates the contribution to the capital return inequality.

The most used risk-adjusted performance is the Sharpe ratio. The Sharpe ratio is first introduced as a criteria of fund performance in Sharpe 1966, calculated as in equation 1.3:

$$SR_i = \frac{RTN_i - Rf}{\sigma_i} \tag{1.3}$$

Rf is the risk-free interest rate, $RTN_i - Rf$ is the risk premium, and σ_i is the standard deviation of capital return rate of portfolio i. Sharpe 1994 revised the Sharpe ratio by letting $\sigma_i = \sqrt{Var(RTN_i - Rf)}$, the standard deviation of the excess return of portfolio i. In this paper, the revised Sharp ratio is used.

For each endowment, I calculate the annual Sharpe ratio by equation 1.4.

$$SR_{it} = \frac{RTN_{it} - Rf_t}{\sigma^E_{it}} \tag{1.4}$$

where, Rf_t is the return of the US government's three-month treasury bills, and $(\sigma^E_{it})^2 = \Sigma_a \Sigma_b \sigma^E_{abt} W^a_{it} W^b_{it}$.[15] In computing the standard deviation of the excess return of endowment i, all the variance and covariance of the excess return of different benchmarks are included. σ^E_{abt} is the covariance of the excess return of benchmark a and b in year t if $a \neq b$, and the variance of the excess return of benchmark a if $a = b$. W^a_{it} is the portfolio allocation weight of asset a.

Since the Sharpe ratio is a theoretical measure on which a rational fund manager is supposed to rely in order to construct the optimal portfolio allocation, it would make more sense to use the ex ante Sharpe ratio, meaning the return and the standard deviation are all measured by ex ante probabilities. However, it is almost impossible to get the expected value in practice. The Sharpe ratio we employ in this paper is the ex post measure.

To construct the standard deviation of each endowment, I estimate the covariance and variance of the excess returns of the benchmark indexes. The estimation method is Expo-

[15] Here I use the temporal variation as the proxy for the risk of assets. Alternatively, I can follow Flavin and Yamashita 2002 to construct the cross-sectional risk measure of assets.

nentially Weighted Moving Average(EWMA), as expressed in equations 1.5:

$$
\begin{aligned}
m^E_{a\tau+1} &= \lambda m^E_{a\tau} + (1-\lambda)(R_{a\tau} - Rf_\tau) \\
u_{a\tau} &= (R_{a\tau} - Rf_\tau) - m^E_{a\tau} \\
(\sigma^E_{a\tau+1})^2 &= \lambda(\sigma^E_{a\tau})^2 + (1-\lambda)u^2_{a\tau} \\
\sigma^E_{ab\tau+1} &= \lambda\sigma^E_{ab\tau} + (1-\lambda)u_{a\tau}u_{b\tau}
\end{aligned}
\tag{1.5}
$$

where λ is the decay parameter, $m^E_{a\tau}$ is the moving average of the excess return of benchmark a, and $u_{a\tau}$ is the deviation of the excess return of asset a from its mean. The initial values of iteration, m^E_{a0}, σ^E_{a0}, and σ^E_{ab0}, are the long run values.[16]

Another thing to notice is that the time period is in quarterly frequency in equation 1.5. However, the Sharpe ratio needs to be in annual frequency for panel regression. I then take the average of the variance and covariance within a year as the annual values that enter the computation of σ^E_{it} in equation 1.4.

There is a concern that the missing data of private equity and venture capital will induce an upward bias in estimating the endowment portfolio volatility, because endowments may use private equity or venture capital to hedge the risk they face in other types of assets. Therefore, the return of these two assets should be negatively correlated with other assets.

[16] The long-run mean, long-run variance and long-run covariance are all for the period 1995-2013 except for the asset Energy and Natural Resource, which is calculated fro 2003-2013 because of the data availability.

However, this concern is unnecessary. Recent academic research shows that private equity and venture capital provides few hedging benefits: Welch 2014 proves that the diversification illusion of private equity comes from the fact that private equity firms underestimate the comovement between private equity and market returns.

Now we can replace RTN_{it} in equation 1.1 with SR_{it}, and run the regression in equation 1.6. The parameter of interest is β_1'. If $\hat{\beta}'_1$ is positive and significantly different from zero, it means that after adjusting for the risk, bigger endowments still outperform smaller ones. Then, besides the risk channel, the information channel must have contributed to the better performance. Otherwise, the risk channel dominates. In other words, there is no secret recipe for the out-performers. They get a higher return simply by loading on more risk.

$$SR_{it} = \alpha_i' + \beta_1' \ln ENDOW_{it} + \Sigma_{t=2003}^{2012} \delta_t' year_t + \varepsilon_{it} \quad (1.6)$$

Table 1.8 shows the regression results of equation 1.6. The upper panel presents the results with the full sample from 2003 to 2013 with different values for decay parameter λ.[17] Although the coefficient β_1' is not statistically significant at a level of 90 percent, the estimates are negative. This tells us after controlling for the risk that the bigger endowments perform no better than the smaller ones, and perhaps even underperform the smaller ones. If we concentrate the estimation on the endowments that are under \$1 billion, this negative correlation between the Sharpe ratio and size becomes even larger for any given λ.

[17]Note that $\lambda = 1$ is the usual case of a constant mean and standard deviation.

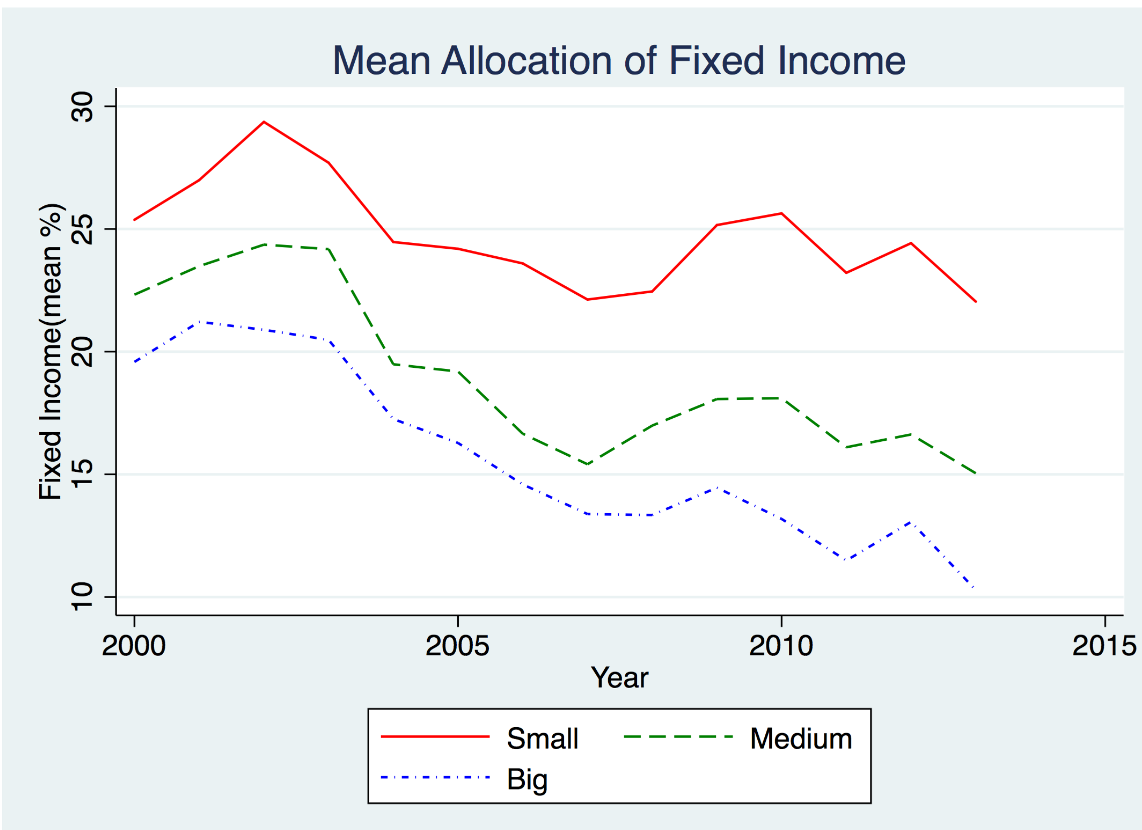
Table 1.8: Regression of Sharpe Ratio on Size

	$\lambda = 0.99$	$\lambda = 0.84$	$\lambda = 0.7$
Full Sample	**2003-2013**		
LENDOW	-0.97	-1.03	-1.41
S.E.	.99	.98	1.09
Obs.	(948, 7162)	(948, 7162)	(948, 7162)
Exclude Endow > 1b	**2003-2013**		
LENDOW	-1.13	-1.18	-1.61
S.E.	1.12	1.11	1.23
Obs.	(908, 6573)	(908, 6573)	(908, 6573)

λ is the decay parameter.
Standard error is heteroscedasticity-consistent, and clustered by university endowment.
NACUBO Endowment-level Data

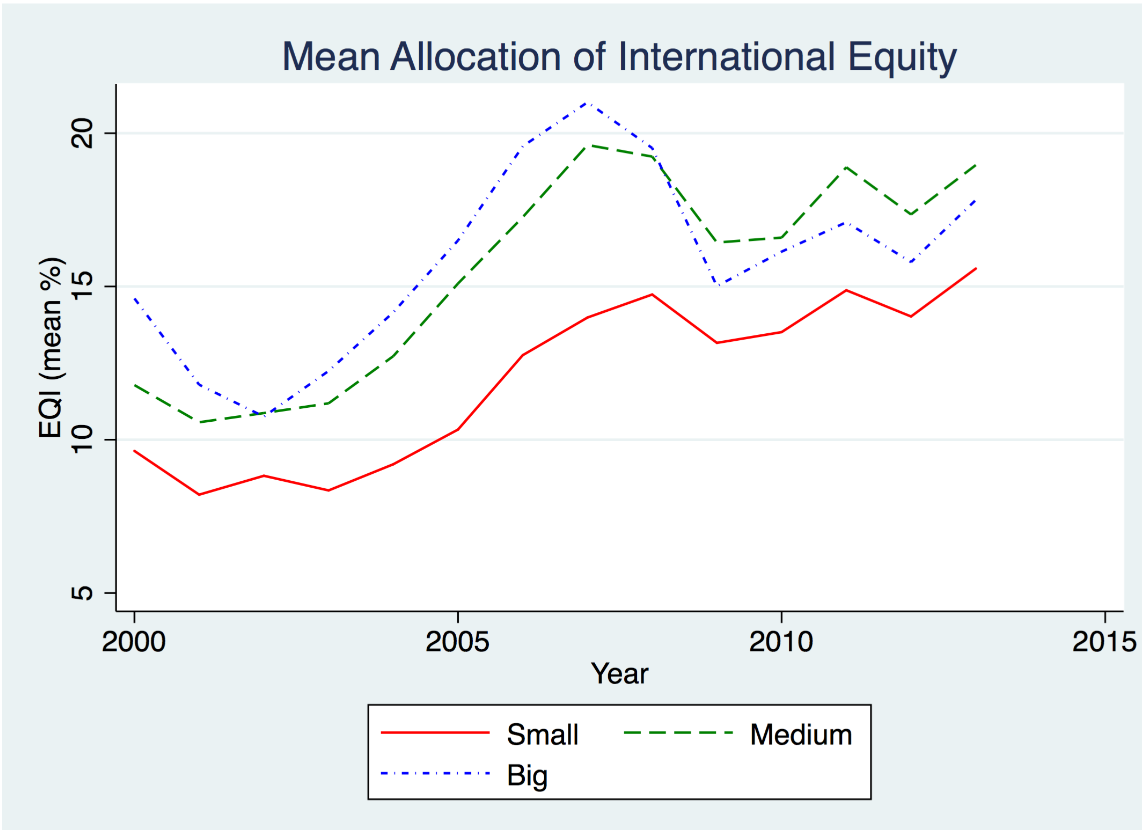
There are other pieces of evidence that risk plays a very important role in determining the capital return for university endowments. Figure 1.2 represents a stable pattern that the bigger an endowment gets, the less weight is allocated to the fixed income. Indeed, Figure 1.3 reveals that the bigger endowments put more weight on international equity compared to smaller ones. Although after the 2008 financial crisis, the biggest endowments have lowered the allocation in risky international equities, they still put more weight in them than the smaller endowments. Table 1.9 tells us that the international equity is one of the most volatile assets, while the fixed income is of very low risk.

Figure 1.2: Mean Allocation of Fixed Income of Different Size of Endowments



Small $100 million and under, medium $100 million - $500 million, big over $500 million
NACUBO Endowment-level Data

Figure 1.3: Mean Allocation of International Equity of Different Size of Endowments



Small \$100 million and under, medium \$100 million - \$500 million, big over \$500 million
NACUBO Endowment-level Data

Figure 1.4 shows the year-to-year regression result of RTN on $\ln ENDOW$. The coefficient $\hat{\beta}_1$ varies a lot. But the general pattern is that when the market is in a boom, the correlation between return and size is positive, such as 2000 and 2004 - 2008.[18] When the market is in a recession, the positive correlation disappears. In year 2009, this correlation is even reversed. This suggests that the bigger endowments may just surf on the wave of the market and expose themselves to more market risk.

[18]The NACUBO data is collected every year in June. Therefore, year 2008 is still considered to be in an economic boom.

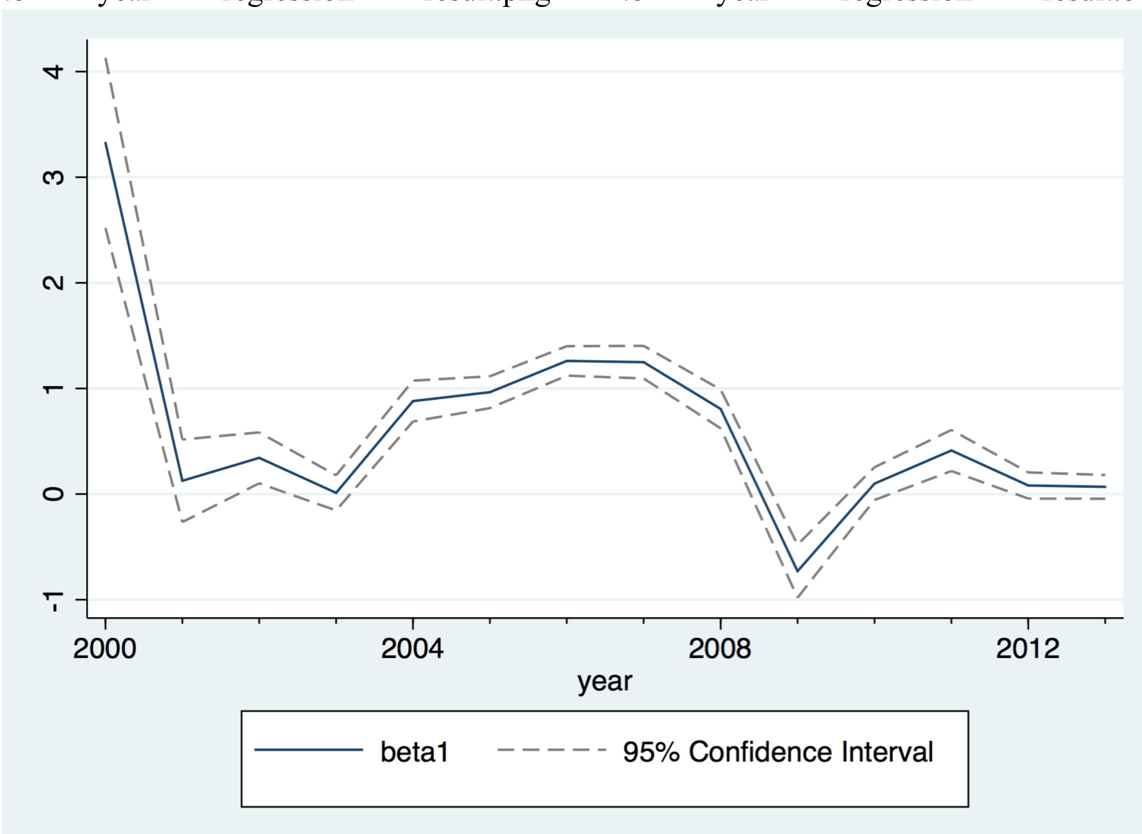
Table 1.9: Standard Deviation of Benchmark Indexes Quarterly Return

year	DE	FI	EQI	PE	ALT	VC	RE	EN	COM	DD	CASH
2000	10.4	1.7	9.7	.	5.9	.	0.84	.	7.6	5.1	0.17
2001	9.9	1.8	9.7	.	5.2	.	0.90	.	7.2	4.4	0.22
2002	11.4	2.0	10.0	.	4.0	.	1.4	.	7.6	3.5	0.43
2003	10.9	1.8	11.2	.	3.1	.	1.0	10.5	6.0	3.7	0.46
2004	9.8	2.0	11.7	.	2.6	.	0.85	10.5	6.5	3.8	0.40
2005	7.4	2.0	9.4	.	2.5	.	1.2	8.4	7.8	3.3	0.31
2006	5.4	1.9	7.8	.	2.4	.	1.3	9.0	8.5	2.8	0.35
2007	4.5	1.8	6.1	.	2.5	.	0.98	8.1	7.0	2.3	0.38
2008	5.1	1.8	6.1	.	2.8	.	1.7	11.7	9.3	3.1	0.36
2009	9.4	2.1	12.8	.	5.9	.	7.0	16.4	17.0	7.1	0.48
2010	11.6	1.8	15.2	.	5.2	.	6.4	14.5	13.6	8.0	0.45
2011	10.8	1.9	13.5	.	4.1	.	5.9	14.4	12.3	5.9	0.35
2012	12.3	1.6	13.6	.	3.8	.	4.4	13.8	10.1	5.7	0.26
2013	9.9	1.6	10.7	.	3.2	.	3.1	10.9	8.6	4.9	0.19
Mean	9.2	1.8	10.5	.	3.8	.	2.3	11.7	9.2	4.5	0.34

Domestic Equities(DE), Fixed Income(FI), International Equities(EQI), Private Equity(PE), Marketable Alternatives(ALT), Venture Capital(VC), Real Estate(RE), Energy and Natural Resources(EN), Commodities(COM), Distressed Debt(DD), Short-Term Securities/Cash(CASH)
From publicly available benchmark indexes

Figure 1.4: Year-to-Year Regression Coefficient of RTN on LENDOW

to year regression result.png to year regression result.bb



NACUBO Endowment-level Data

Controlling for the Information Channel

In this subsection, I present a method to explicitly control for the information channel. The takeaway message is that the information channel is negligible relative to the risk channel in determining capital return inequality. In the previous subsection, I demonstrate that risk channel dominates the contribution to capital return inequality.

The main assumption is that benchmark indexes contain all the public information and university endowments deviate from the benchmarks because they own some private information. If each endowment simply relies on the public information and traces only benchmarks, the synthetic return and the actual return should be exactly the same. And the coefficient $\hat{\beta}_1$ should be the same as well, using either the synthetic return or the actual return in regression (1). The discrepancy between synthetic return and actual return demonstrates that some endowments deviate from the benchmark indexes. And we do see in Table 1.7 that after excluding the endowments above \$1 billion, the coefficient $\hat{\beta}_1$ obtained with the synthetic return is much closer to that of the actual return. This piece of evidence suggests that bigger endowments deviate more from the benchmark indexes than smaller ones.

Therefore, I construct a proxy for the private information in equation 1.7:

$$|Diff|_{it} = |RTN_{it} - RTN_{it}^{syn}| \tag{1.7}$$

The absolute value in equation 1.7 comes from the assumption that no endowment can have less information than the publicly available market information. This proxy for the private information is not perfect though. It would be ideal to know the disaggregate return of individual assets for each endowment. Then we can use the difference between actual return of asset a and the benchmark return of asset a as a proxy for an endowments' private information in a particular type of asset. From there, we could aggregate to construct the total private information. However, the data at my disposal is only total return.

Including the proxy of the private information in panel regression, we now have regression equations 1.8:

$$RTN_{it} = \alpha_i + \beta_1 \ln ENDOW_{it} + \beta_2 |Diff|_{it-1} + \Sigma_{t=2004}^{2012} \delta_t year_t + \varepsilon_{it}$$

$$SR_{it} = \alpha_i' + \beta_1' \ln ENDOW_{it} + \beta_2' |Diff|_{it-1} + \Sigma_{t=2004}^{2012} \delta_t' year_t + \varepsilon_{it} \tag{1.8}$$

The reason to use $|Diff|_{it-1}$ instead of $|Diff|_{it}$ is to avoid the potential endogeneity problem in the regressions.

The results of regression (8) are reported in the upper panel of Table 1.10 , and the results of regression (9) in the lower panel. The loading on the information channel $\hat{\beta}_2$ and $\hat{\beta'}_2$ is negative and close to zero.

It is difficult to compare $\hat{\beta}_1$ and $\hat{\beta}_2$ directly since the variables $\ln ENDOW$ and $Diff$ have different units. However, we can compare their separate contributions to the capital income inequality. Since the information channel is controlled, the residual loading on size can be considered to be the loading on the risk channel in equations 1.8.

Table 1.10: Regression of Return and Sharpe Ratio on Size and Information

Dep.	Indep.	Full Sample	Exclude Endow $>$ 1b
RTN	**LENDOW**	2.29(.608)***	2.53(.645)***
	L.Diff	-.040(.0169)**	- .045(.0176)**
SR	**LENDOW**	-1.63(1.590)	-1.75(1.706)
	L.Diff	-.054(.046)	-.063(0.056)
	Obs.	(867, 5888)	(819, 5342)

The decay parameter is $\lambda = 0.84$ in this table.
Standard Error is heteroscedasticity-consistent, and clustered by university endowment.
NACUBO Endowment-level Data

In the whole data set, the largest 10 percent of the endowments have an average $\ln ENDOW = 21.91$, while the smallest 10 percent yield $\ln ENDOW = 16.05$. Therefore, the size difference between the two groups is 5.86, and the contribution of the risk channel to the return difference of the two groups is $5.86 \times \hat{\beta}_1 = 13.4\%$. The information channel difference between the same two groups is 1.65, which indicates that the information channel contribution to the return differences is merely $1.65 \times \hat{\beta}_2 = -0.066\%$.

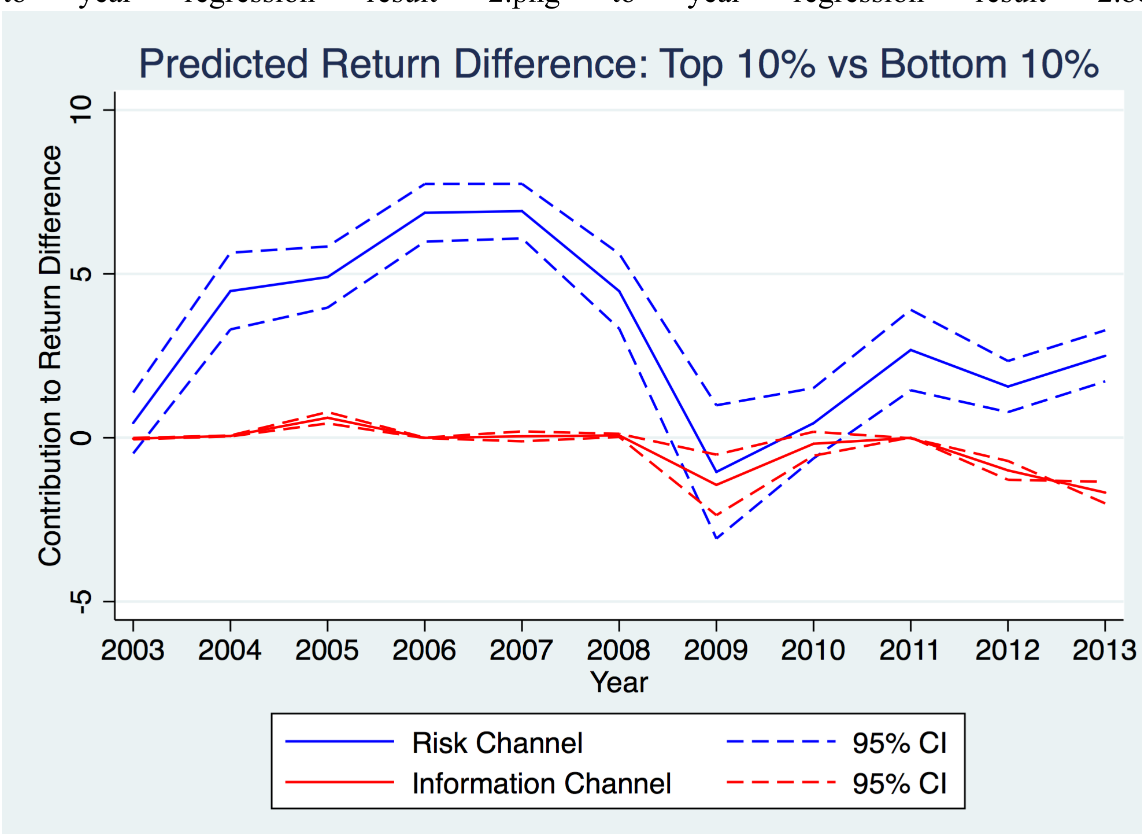
There is even more evidence supporting the conclusion that the information channel plays little role in determining capital return inequality. First, I run the year- to-year regression as in equation 1.9,

$$RTN_t = \alpha + \beta_1 \ln ENDOW_t + \beta_2 |Diff|_{t-1} + \varepsilon_t \tag{1.9}$$

This is not a panel regression anymore, so there is no fixed effect. The regression result can be used to compute the time-varying contribution of different channels to the capital return inequality. Figure 1.5 represents the contribution of two channels to the return difference between the top decile endowments and bottom decile ones in terms of the endowment size. The curve representing the information channel is close to zero compared to the other representing the risk channel. In some years, such as 2012 and 2013, the information channel is indeed comparable to the risk channel, but the contribution of the former is nonetheless negative.

Figure 1.5: Year-to-Year Contribution to Return Difference between Two Channels

to year regression result 2.png to year regression result 2.bb



NACUBO Endowment-level Data

Second, I run the regression as shown in equation 1.10:

$$Diff_{it} = \gamma_i + \theta_1 \ln ENDOW_{it} + \Sigma_{t=2003}^{2012} \delta_t year_t + \varepsilon_{it} \tag{1.10}$$

The dependent variable is $Diff_{it}$, not the absolute value. The idea is that if the private information has little impact on the capital return, public information should capture most of the variation of the returns. So the discrepancy between the actual return and synthetic return (or the excess return) should not depend on endowment size. Table 1.11 shows this link does exist: The coefficient $\hat{theta}_1$ is not statistically different from zero. After excluding forty of the largest university endowments with size above $1 billion, the coefficient is virtually zero.

Table 1.11: Regression of Excess Return on Size

Dep.	**Indep.**	**Full Sample**	**Exclude Endow $>$ 1b**
Diff	**LENDOW**	0.23(.38)	0.08(.38)
	Obs.	(948, 7162)	(908,6573)

The decay parameter is $\lambda = 0.84$ in this table.
Standard error is heteroscedasticity-consistent, and clustered by university endowment.
NACUBO Endowment-level Data

1.5 Robustness Check

In this section, I show alternative evidence that also supports the view that the risk channel rather than the information channel determines capital return inequality.

Total (static) Sharpe Ratio

In this subsection, I deal with the concern that the risk measured as the weighted volatility of the excess return of benchmark indexes only captures the variation of between-asset allocation, while ignoring the within-asset allocation. For example, let us say there are two endowments have the same allocation of portfolio in terms of eleven explicit asset types: Both put 50 percent in domestic equities and 50 percent in bond, and zero in all other assets. Based on this measure of risk, we would conclude that they have the same risk. However, it could be that one endowment allocates all the weight of domestic equities in riskier stocks and the other in safer stocks. So the true risk they face could potentially be very different.

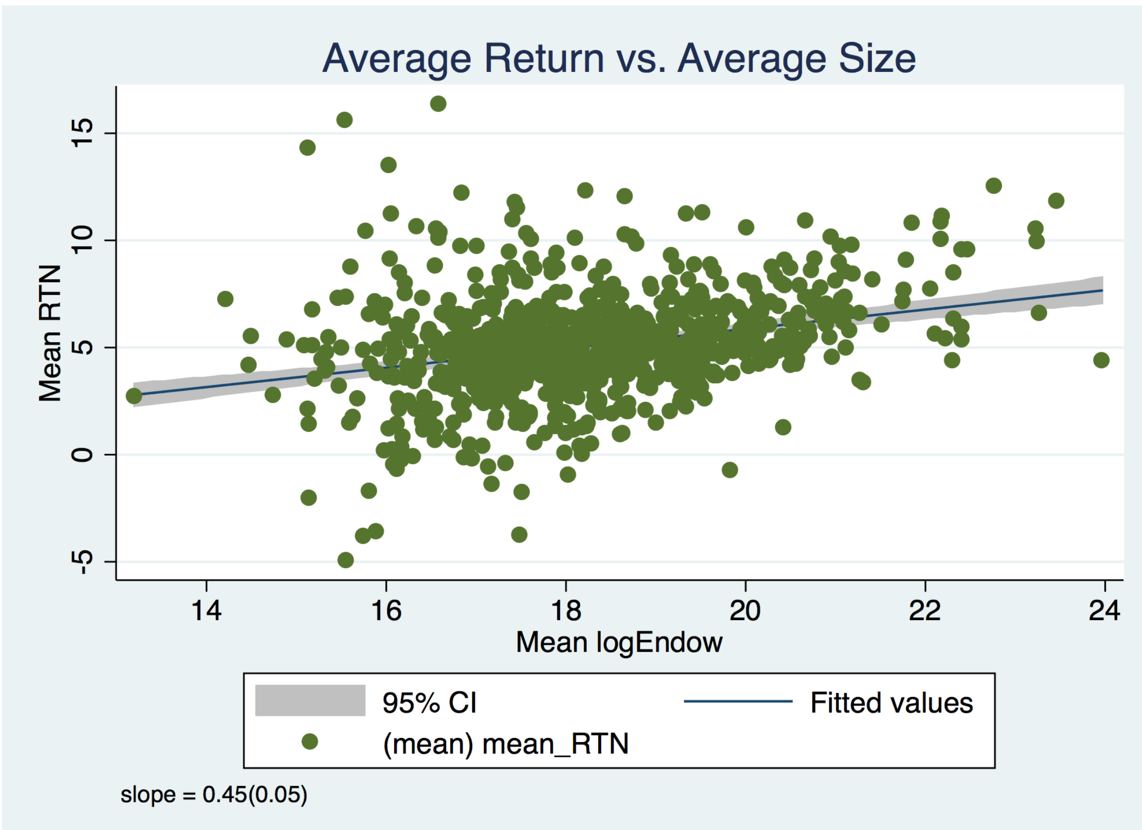
I present an alternative risk measure and an alternative Sharpe ratio to alleviate the concern. This alternative Sharpe ratio is defined in equation 1.11:

$$SR_i^T = \frac{\overline{RTN}_i - \overline{Rf}}{\sigma_i^{ET}} \tag{1.11}$$

The superscript of Sharpe ratio T means that this measure takes the total risk into consideration. And since it is not a time-varying variable, there is no time subscription t. $\overline{RTN}_i$ stands for the time average of total net return of endowment i from year 2000 to 2013. $\overline{Rf}$ is the time average return of the US government's three-month treasury bills from the same period. σ_i^{ET} is the total volatility, measured as the standard deviation of excess return of endowment i. I call SR_i^T the total Sharpe ratio and σ_i^{ET} the total volatility or the total risk.

In this setting, there is no panel data. The data set is degenerated into a purely cross-section one. The X axes of Figures 1.6 and 1.7 are the same, the time average of endowment size;[19] while the Y axes are respectively $\overline{RTN}_i$ and SR_i^T. In order to ensure that the standard deviation makes sense, I only keep the endowment that has at least 3 observations in the dataset.

Figure 1.6: Average Return vs. Average Size

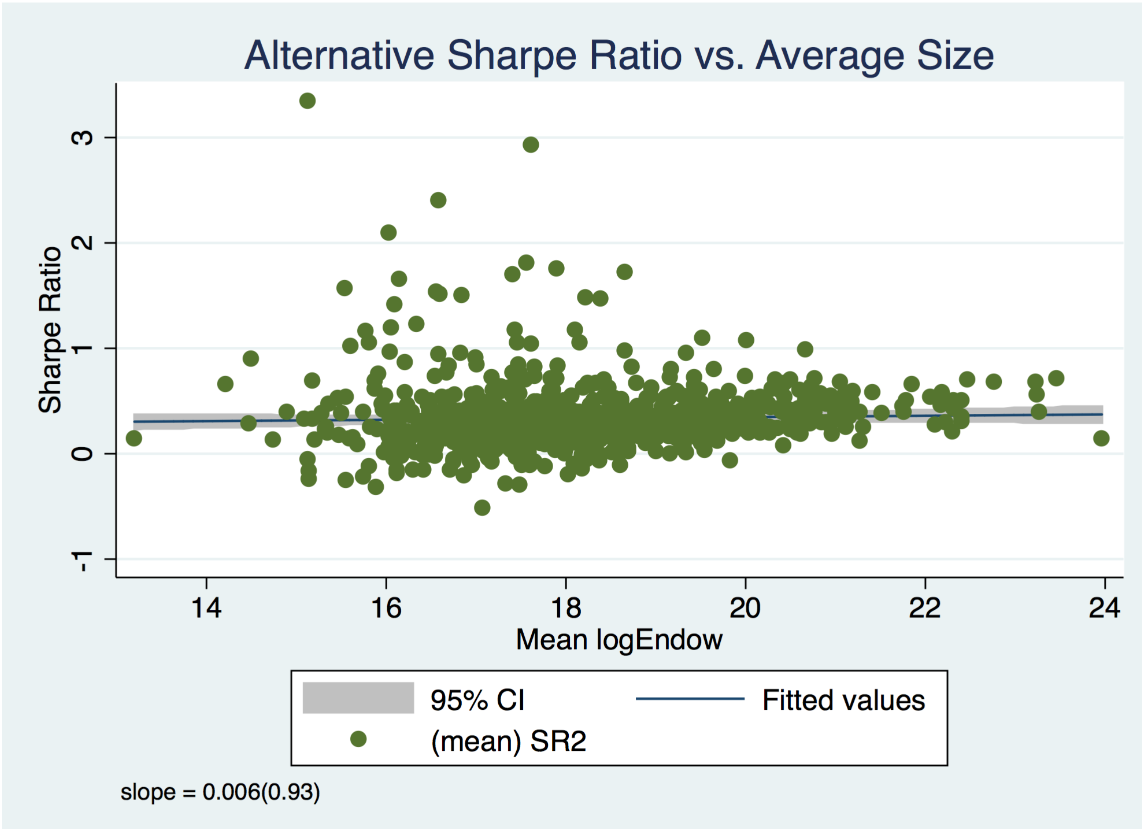


Each point in the graph stands for an endowment.
Only endowments with at least three observations are included.
Three outliers are excluded from the graph. If They were included, the slope is slightly bigger: slope = 0.46(0.051)
NACUBO Endowment-level Data

The slope of the two graphs and the corresponding t-statistics are also specified in the southwest corner. The correlation between the average return and average size is both positive and statistically significant. Moreover the numeric value 0.45 is close to the result

[19] The endowment is measured in log term.

Figure 1.7: Alternative Sharpe Ratio vs. Average Size



Each point in the graph stands for an endowment.
Only endowments with at least three observations are included.
Three outliers are excluded from the graph. If They were included, the slope would become slightly negative: slope = -0.019(0.020)
NACUBO Endowment-level Data

in column 2 of Table 1.4. However, after we control for the risk, Figure 1.7 shows no correlation between the size and the Sharpe ratio.

Explicit Risk Channel vs. Explicit Information Channel

In this subsection, I explicitly show the regression of return on both the risk channel and the information channel, rather than treating the risk channel as a residual channel as in equations 1.8.

More specifically, I run the regressions in equations 1.12:

$$RTN_{it} = \alpha_i'' + \beta_1''\sigma_{it} + \beta_2''Diff_{t-1} + \Sigma_{t=2004}^{2012}\delta_t''year_t + \varepsilon_{it}$$
$$RTN_{it} = \alpha_i''' + \beta_1'''\sigma_{it}^E + \beta_2'''Diff_{t-1} + \Sigma_{t=2004}^{2012}\delta_t'''year_t + \varepsilon_{it} \tag{1.12}$$

The difference between the two equations above is the standard deviation used. The second equation uses σ_{it}^E, which is the same as is defined in equations 1.5, The superscript E stands for the excess return of the endowment return in comparison to the risk-free asset. The first set of equations use an alternative time-varying risk measure σ_{it}, where $\sigma_{it}^2 = \Sigma_a\Sigma_b\sigma_{abt}W_{it}^aW_{it}^b$. The superscript E is dropped to indicate that it is no longer the excess return but the actual return of the benchmark indexes that is involved in the calculation of the risk. The computation of σ_{it} is shown in equation 1.13

$$m_{a\tau+1} = \lambda m_{a\tau} + (1-\lambda)R_{a\tau}$$
$$v_{a\tau} = R_{a\tau} - m_{a\tau}$$
$$\sigma_{a\tau+1}^2 = \lambda\sigma_{a\tau}^2 + (1-\lambda)v_{a\tau}^2 \tag{1.13}$$
$$\sigma_{ab\tau+1} = \lambda\sigma_{ab\tau} + (1-\lambda)v_{a\tau}v_{b\tau}$$

where λ is the decay parameter, $m_{a\tau}$ is the moving average of the return of the benchmark index a, and v_{at} is the deviation of the return of asset a from the mean. The initial values of iteration, m_{a0}, σ_{a0}, and σ_{ab0}, are the long run values. Actually, since the return of risk free asset is very stable, σ_{it} is very similar to σ_{it}^{E}.

The results are shown in Table 1.12. No matter which risk measurement is used, the load on the risk channel does not vary much and is around 0.60. And the load on the information channel is around -0.065. The average contribution of the risk channel to the return is therefore 3.27 percent, while that of the information channel is merely 0.6 percent.

Table 1.12: Regression of Return on the Risk Channel and Information Channel

Dep.	**Indep.**	**Full Sample**	**Exclude Endow > 1b**
RTN	σ	.60(.101)***	.59(.106)***
	L.Diff	-.065(.0165)***	-.066(.0182)***
RTN	σ^{E}	.62(.100)***	.61(.106)***
	L.Diff	-.066(.0165)***	-.067(.0182)***
	Obs.	(867, 5888)	(819, 5342)

The decay parameter is $\lambda = 0.84$ in this table.
Standard Error is heteroscedasticity-consistent, and clustered by university endowment.
NACUBO Endowment-level Data

1.6 Conclusion

I would like to conclude my paper with a story written by Mark Twain in 1906 called *\$30,000 Bequest*. Living through the Gilded Age in the US, which was the last three decades of nineteenth century, Twain witnessed the increasing inequality of that era. His story is about a middle-class couple with an annual income of \$800 in a small town. Their typical investment was to buy land and then resell it to newcomers to the town. One day, they heard from their distant uncle that they would get a $30,000 bequest after he died. Merely the news itself was already enough for them to make bolder investment strategies. With the vain hope that they would someday have such a huge amount of money, they started to envision investing in very risky assets, such as coal mines and stocks. They did not have more information on those assets and were simply attracted by the higher return. Alas, of course, this was only a dream for them. They did not receive any bequest from their uncle since he had died years before. The point of the story is to show that people are willing to bear more risk in investments once they become richer and this is consistent with the empirical finding in this paper that higher capital return comes from more risk.

Chapter 2

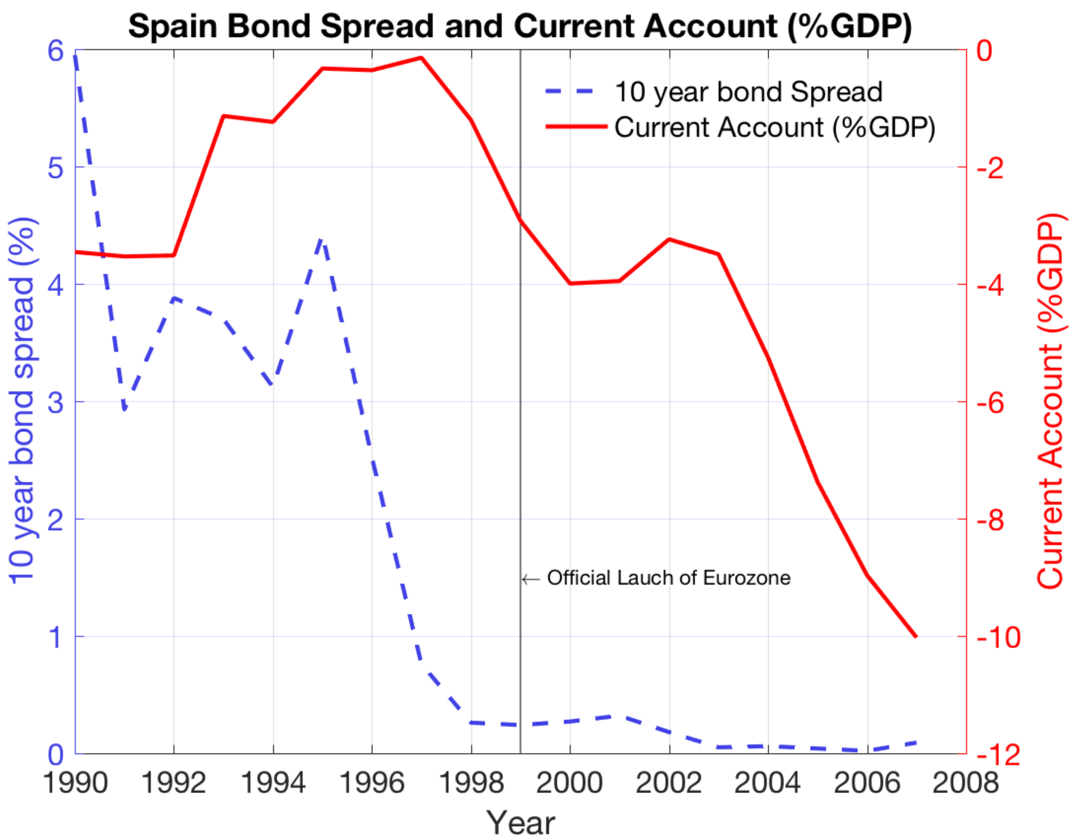
TFP Declines: Misallocation or Mismeasurement?

2.1 Introduction

The Eurozone integration (officially started in 1999, expectation started in 1996) was accompanied by plummeting of borrowing cost and continuing deterioration of the current accounts in Spain and other southern European countries, as shown in Figure 2.1. The economy was booming, but its measured total factor productivity (TFP) was decreasing. Researchers and policy makers often blame this negative correlation between the expansion of the economy and TFP growth on capital/resource misallocation. The idea is that the cheap credit flowed more into less productive firms and the compositional change of the economy brought down the average productivity.

This paper challenges the view that the misallocation channel is the main explanation for the TFP drop, and it proposes that the labor-quality mismeasurement channel is a more reasonable explanation. The labor-quality mismeasurement channel ascribes the measured TFP drop to the lower efficiency of the incoming labor compared to the existing labor force in expanding sectors. The idea is that the TFP calculation does not fully capture labor quality, which is automatically translated to the TFP measured as a residual. Although

Figure 2.1: Interest Rate Spread and Current Account



Raw data: WDI

The definition of spread: the difference between the bond yield of Spain and Germany

the labor quality can be measured to some extent with limited observable characteristics, such as education, age, and gender, other dimensions such as tenure are usually not widely observed.

The argument for labor-quality mismeasurement channel is developed in five steps. First, I show that TFP decline is much more severe in expanding sectors (such construction and real sector) than in relatively stable sectors (such as manufacturing), using both aggregate data and firm-level data. The aggregate TFP data is from Klems, calculated under the assumption of the constant return to scale. The firm-level TFP is calculated using Amadeus data obtained from vintage discs. The firm-level TFP measurement methodologies are built on Levinsohn and Petrin 2003 and De Loecker 2011.[1] Although constant return to scale is not imposed in the firm-level TFP estimation, the result is very close to it.

Second, the growth of dispersion of the marginal revenue product of capital (MRPK) suggests there is more misallocation of capital in non-expanding sectors than in expanding sectors. Using firm-level data, I demonstrate that the growth of dispersion of the MRPK is more significant in non-expanding sectors than in expanding sectors. The dispersion of the MRPK is usually considered as an indication of the capital misallocation following Chang-Tai Hsieh 2009, and it serves as the main evidence for the papers (such as Gopinath et al. Forthcoming, and Garcia-Santana et al. 2016) arguing that capital misallocation caused the TFP stagnation problem in southern Europe. If capital misallocation is the real explanation of the TFP drop, we should observe more growth of the dispersion of the MRPK in expanding sectors than in non-expanding sectors. [2]

Third, decomposition of the TFP growth indicates that the between-firm TFP growth is negligible compared to the within-firm growth in the sub-sample of stayers. Compared to the dispersion growth of the MRPK, this is a more direct piece of evidence showing that the capital misallocation channel cannot be the main explanation, but the labor-quality mismeasurement channel can be. If capital misallocation is the main channel, we should observe

[1] I only discuss the mismeasurement of the labor quality but not the mismeasurement of the capital quality is because studies like Sakellaris and Wilson 2004, show that newly invested capital has, on average, higher quality than the existing one. Therefore, if we take into account capital quality mismeasurement, then the TFP growth paths of the expanding sectors and non-expanding sectors would be even more divergent.

[2] There are papers that both support Chang-Tai Hsieh 2009 and argue against it. Whether dispersion of the MRPK is a good measure of the capital misallocation or not, the misallocation channel as the main explanation for the TFP drop is inconsistent with data.

that resources move more into less productive firms. In other words, the decomposition result should reveal that between-firm TFP change accounts for the lion's share of the TFP drop. The data shows otherwise: both in expanding sectors and in non-expanding sectors, the between-firm change of TFP is miniscule. The within-firm TFP change accounts for one-third of the total TFP drop in expanding sectors but increased slightly in expanding sectors. This observation is consistent with the labor-quality mismeasurement channel.

Fourth, using the worker-firm matched data, I establish that the limited observable characteristics of workers are not sufficient to control for labor quality and that labor quality beyond education, age and gender deteriorates in expanding sectors but not in non-expanding sectors. The worker-firm matched dataset is from the Eurostat Structure of Earnings Survey. The characteristics that KLEMS dataset employs to control for labor quality are education, age and gender, which only account for one-third of the wage variation in the manufacturing sector and less than 20 percent of the wage variation in the construction sector. Worker's tenure (which can be thought as an imperfect proxy for experience), especially that of firm managers, has decreased significantly in expanding sectors but has increased in non-expanding sectors. Moreover, the distribution of unobserved labor quality is backed out by taking out firm fixed effects and observed labor characteristics from the real hourly wage, which can be fed into the model later. More specifically, by running the regression of hourly wage on firm characteristics, the distribution of the residual is taken as the distribution of labor quality.

Last but not least, I build a model featuring both the misallocation channel and the mismeasurement channel and calibrate it using the micro-level data. The model shows that once the labor quality mismeasurement is properly measured, the TFP drop is small. The model works as follows: a negative interest rate shock (Eurozone integration) enables low-productivity firms in the non-tradable sector to enter the production by borrowing. This brings down the average productivity of this sector. Moreover, borrowing costs for non-tradable firms are also lowered and allows them to borrow more; thus, the sector expands. The tradable sector is not affected by the shock, since it is assumed that the tradable firms are far less financially constrained. Therefore, there is no expansion in this sector. The expansion in the non-tradable sector increases base wage and attracts the labor from the tradable sector. The marginal worker entering the non-tradable sector is less efficient compared to the average existing workers, while the way the TFP is calculated treats incoming workers the same as the existing ones. So, the lower efficiency of the worker is translated into lower measured TFP. The existence of the mismeasurement channel makes the true TFP drop much less acute than the measured TFP suggests.

Related Literature. This paper contributes to a body of work that studies the measured TFP drop during the Eurozone integration period. Compared to the papers that argue capital misallocation is the main channel for measured TFP drop, this paper studies an additional labor quality mismeasurement channel and finds it to be more important. Reis 2013, Calligaris 2015, Dias, Marques, and Richmond 2016, Garcia-Santana et al. 2016, Cette, Fernald, and Mojon 2016 and Gopinath et al. Forthcoming all argue that capital misallocation is the main reason that TFP has declined in southern Europe. Cette, Fernald, and Mojon 2016 provides aggregate evidence based on VAR analysis that interest rate drop triggers the productivity decline. But this correlation between negative interest rate shock and productivity change is consistent with the mechanism in my model as well. Calligaris 2015 and Gopinath et al. Forthcoming both use firm-level data and provide evidence that removing the heterogeneity of productivity can substantially increase the aggregate productivity substantially. The analysis, however, is restricted to the manufacturing sector and thus ignores the significant difference between expanding sectors and non-expanding sectors. Dias, Marques, and Richmond 2016 and Garcia-Santana et al. 2016 extend the misallocation to multiple sectors with administrative data. However Dias, Marques, and Richmond 2016 provides only the dispersion of the productivity, which is not necessarily due to capital misallocation. Garcia-Santana et al. 2016 posits that more government influence is associated with more misallocation. Reis 2013 argues that capital misallocation in the non-tradable sector is more severe than that in the tradable sector based on the inference from aggregate data.

There are alternative theories explaining the TFP drop during the Eurozone integration period. Benigno and Fornaro 2014 assumes that labor employed by the tradable sector has a learning-by-exporting effect which depends on the size of employment due to the positive externality. This theory is based on the assumption that the tradable sector has to shrink in the absolute term, while in the data we observe only the relative shrinkage of the tradable sector. Antonia Diaz 2016 shows the correlation between the governmental subsidy to residential structure purchase and the TFP drop. It takes the measured TFP drop as given and estimates the subsidy has to be 50 percent of the price of residential structure to generate the observed TFP dynamics. Challe, Lopez, and Mengus 2016 argues the decline of the quality of institution due to the capital inflow can explain the dismal TFP performance.

However, it does not distinguish the institutional quality among different sectors.

The labor quality mismeasurement channel in my model can be linked to two bodies of work. Theoretically, I incorporate the partial equilibrium model of Young 2014 into a general equilibrium model. The economic narrative that labor quality in an expanding sector could deteriorate dates back to Roy 1951. The empirical part in this paper is very related to the analysis pioneered by Abowd and Kramarz 1999 using worker-firm matched data. Card et al. 2016 is a recent paper in the same literature. These papers argue that wage variation can be decomposed to firm characteristics and worker characteristics.

Other papers address the connection between the business cycles and the quality of the labor force. My paper discusses the labor quality deterioration during a boom of the economy. Solon, Barsky, and Parker 1994 finds that true procyclicality of real wage is obscured in aggregate time series because of a composition bias due to more low-skill workers during expansions. Mulligan 2011 studies the higher labor productivity during the recession of 2008-9, and part of the reason is that the remaining labor force had higher quality relative to that before the recession. Mueller 2017 shows that in recessions the pool of unemployed tends to have workers with higher quality.

Another strand of literature to which my paper connects to is the literature of firm-level TFP measure. My estimation of firm-level TFP follows methodologies in Levinsohn and Petrin 2003, De Loecker 2011 and Ackerberg, Caves, and Frazer 2015. The origin of the literature can be traced back to Olley and Pakes 1996. The firm-level TFP measure in my paper confirms the widely studied phenomenon of the very dispersed firm-level TFP measure discussed thoroughly in Syverson 2011.

My paper also links to the literature studying whether static dispersion of the MRPK is a good measure of capital misallocation. Chang-Tai Hsieh 2009 argues that it is a very good indicator of capital misallocation and that reducing dispersion could lead to a productivity increase and an output boost. However, there are papers arguing that other reasons could lead to the dispersion of the MRPK. For example **DeLoeckeretal2014** finds that capital adjustment cost can explain 80-90 percent of the cross-industry and cross-country variation in the dispersion of the MRPK. Bils, Klenow, and Ruane 2017 finds that measurement error plays a big role in explaining measured misallocation. My paper does not take a stand in this debate. Whether the dispersion of the MRPK is a good measure of capital misallocation or not, I instead show that the misallocation channel cannot explain the TFP drop during the Eurozone integration period.

The remainder of the paper is organized as follows. Section 2.2 shows stylized facts using aggregate data and calculates the dual measure of the TFP to argue against a possible explanation that measured TFP growth reflects the markup growth. Section 2.3 employs the Spainish firm-level data to show that capital misallocation is not the right explanation and that labor-quality mismeasurement might be the dominant channel. Section 2.4 provides evidence that labor quality does deteriorate in expanding sectors but not in non-expanding sectors. Section 2.5 presents the model. Section 2.6 shows the calibration and the numerical result. Section 2.7 concludes.

2.2 Aggregate Time Series Evidence on TFP Decline

In this section, I show using aggregate data that measured TFP declined or stagnated, especially for expanding sectors .

The aggregate time series data presented in this section are from KLEMS. The KLEMS dataset estimates the TFP mainly for European countries on the two-digit sectoral level. It has different release dates, the one used here is the 2009 release[3]. There are two reasons why I use the 2009 release instead of releases of other years. First, the 2009 release provides the best combination of the temporal coverage and geographical coverage. Since this paper primarily studies the booming period before the 2008 great recession, the 2009 release, with observations until 2007, fits the purpose very well. Moreover, the 2009 release has a lot more geographical coverage, as it includes countries such as Japan and Korea. The two countries experienced booms in certain sectors during the 1990s. Then we can see if what we observe in Europe can be observed elsewhere in a different time period. Second, the 2009 release is the latest release that divides the sector based on the ISIC Rev.3 or NACE 1.1 standard, which is in perfect consistency with the firm-level data that I will show in the next section.

Primal Measure of TFP

The TFP estimation method used in the KLEMS dataset is the primal measure. It assumes that the production function is a constant return to scale Cobb-Douglas function. Thus, the

[3]The newest release is 2016. Before that, there were the 2012 release, the 2009 release, the 2008 release and the 2007 release.

TFP growth will be measured as the growth rate of the Solow-residual:

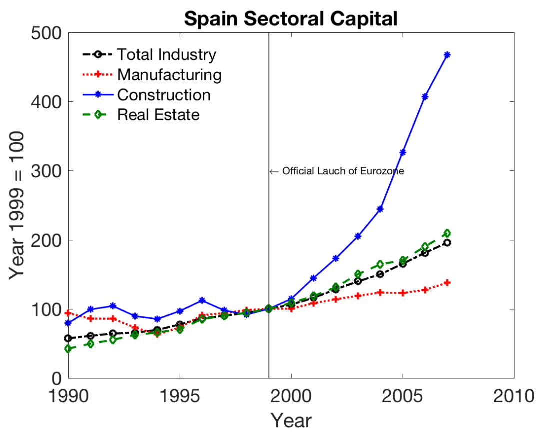
$$\Delta \ln A_{st} = \Delta \ln Y_{st} - \bar{s}^K_{st} \Delta \ln K_{st} - \bar{s}^L_{st} \Delta \ln L_{st},$$

Constant return to scale implies $s^L_{st} + s^K_{st} = 1$. Capital stock is measured using the perpetual inventory model, and labor is measured by the limited quality adjusted labor index. We will discuss more how the labor measured is problematic in terms of labor quality control. O'Mahony and Timmer 2009 provides more detailed information about how KLEMS measures aggregate sectoral level TFP.

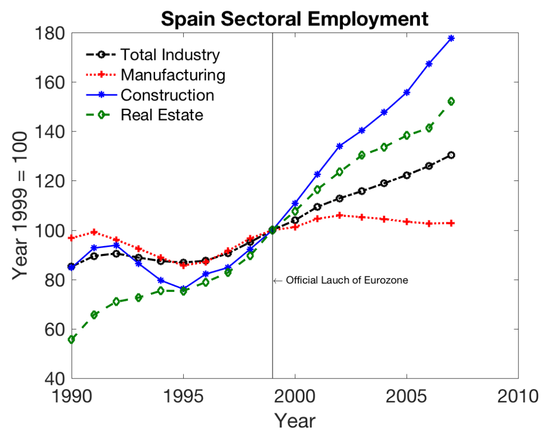
Figure 2.2 plots the sectoral level GDP, capital stock, labor employment and TFP. The black dash-dot line represents for the total industry, the red dotted line the manufacturing sector, the blue solid line the construction sector and the green dashed line the real estate sector.

Subfigures (a) and (b) show that the expansion of the manufacturing sector was mild in any measure compared to that of the construction sector and the real estate sector. In 2007, the real capital stock in the construction sector was almost five times higher than that of 1999; labor employment was almost two times higher. Contrastingly, the manufacturing sector stayed stable. The real capital stock increased nearly 40 percent, and labor employment barely 3 percent. Now turning to the GDP growth in subfigure (c), the difference between the construction sector and the manufacturing sector is much smaller, a 75 percent increase for the former, and a 30 percent increase for the latter. The trends in the subfigures (a), (b) and (c) give rise to the measured TFP trend in subfigure (d). The TFP of the construction sector dropped by more than 10 percent in less than 10 years, while that of the manufacturing sector declined by very little.

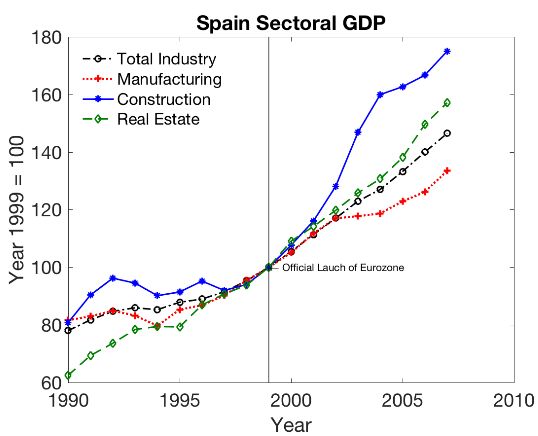
Figure 2.2: Factor Inputs, Output and TFP



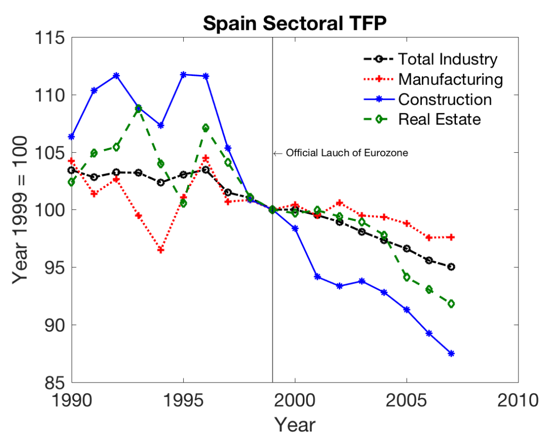
(a)



(b)



(c)



(d)

Raw data: KLEMS
1999 TFP is normalized to 100

Evidence from more countries shows that the same phenomenon is not only observed in Spain, but also in other southern European countries as well. In all the four countries[4] presented in Table 2.1, there exists a negative correlation between the sectoral expansion and the TFP growth. On the left panel of Table 2.1, I list the three most expanded sectors on the one-digit level in terms of the relative labor growth; on the right panel, I list the three least expanded sectors for Portugal, Spain, Ireland and Italy. One striking difference is that the measured TFP declines much more for the sectors experiencing relatively greater expansion.

Searching in the KLEMS dataset results in a finding of three other countries/periods experiencing a huge drop of TFP in fast expansionary sector: Finland from 1984 to 1990, Japan from 1986 to 1991, and Korea from 1988 to 1997. I choose the period systematically: the stopping point is the year before the documented year of the crisis, and the starting point is the year when current account trend reverses. In Table 2.2, I list the two most expanded sectors on the left panel, and the manufacturing sector on the right panel. Sandal 2004 documents the Nordic banking crisis in the early 1990s in Finland, Norway, and Sweden. It attributes the cause to the strong credit and asset price booming before that. There is a huge expansion of real estate sector such that the relative employment increases 4.0% annually between 1984 and 1990 in Finland,[5] with an annual TFP drop at 2.64 percent. The annualized growth rate of relative employment of manufacturing sector is -2.68 percent, while the TFP increases at 3.13 percent per year. Shiratsuka 2005 documents the asset price

[4] They are four countries in the GIIPS group. Greece is not presented due to data availability.

[5] Norway is not in the KLEMS 2009 release and the data of Sweden does not date back to the early 1980s.

bubble in Japan in the 1980s. The same observation appears again, as a fast-expanding real estate sector coexists with negative measured TFP growth. Radelet and Sachs 1998 analyzes the East Asia financial crisis and its prelude, in which an expanding real estate sector and hotel/restaurant sector have experience a continuous measured TFP decline.

Table 2.1: Expansion and TFP Growth (1999 - 2007 Annualized)

	Most expanding			Least expanding		
Countries	**Sectors**	$\Delta \ln \frac{L_{st}}{L_t}$ (%)	$\Delta \ln TFP_{st}$ (%)	**Sectors**	$\Delta \ln \frac{L_{st}}{L_t}$ (%)	$\Delta \ln TFP_{st}$ (%)
Portugal	Real estate	2.57	-4.81	Utility	-5.51	-0.29
	Hotels & Restaurants	1.66	-2.43	Finance	-3.12	4.32
	Wholesale & Retail	1.39	-2.38	Manufacturing	-2.59	-0.72
Spain	Construction	3.36	-1.7	Mining & Quarrying	-4.29	0.52
	Real estate	2.18	-1.22	Manufacturing	-2.98	-0.14
	Hotels & Restaurant	1.94	-2.63	Utility	-2.21	0.19
Ireland	Construction	4.82	-2.74	Agriculture	-7.76	2.25
	Community service	1.45	-1.84	Utility	-4.41	-0.42
	Mining & Quarrying*	0.93	-0.87	Manufacturing	1.31	4.93
Italy	Real estate	3.35	-0.71	Utility	-2.59	-0.13
	Construction	2.67	-1.21	Agriculture	-1.55	-0.55
	Hotels & Restaurant	2.56	-2.27	Manufacturing*	-1.48	-0.13

Raw data: KLEMS
All the numbers are in percentages. The growth rate of Portugal is calculated between 1999 and 2005, others 1999 - 2007
* For Ireland, Mining & Quarrying is the fourth most expanded sector. For Italy, Manufacturing is the fifth least expanded sector.

Table 2.2: Other Booming Periods (Annualized)

	Most expanding			Least expanding		
Countries	**Sectors**	$\Delta \ln \frac{L_{st}}{L_t}$ (%)	$\Delta \ln TFP_{st}$ (%)	**Sectors**	$\Delta \ln \frac{L_{st}}{L_t}$ (%)	$\Delta \ln TFP_{st}$ (%)
Finland	Real estate	4.0	-2.64	Manufacturing	-2.68	3.13
(1984-1990)	Community services	1.75	-0.7			
Japan	Real estate	4.48	-2.14	Manufacturing	-0.41	3.82
(1986-1991)	Hotels & Restaurants	1.51	-1.27			
Korea	Real estate	11.72	-2.09	Manufacturing	-4.26	4.20
(1988-1997)	Hotels & Restaurants	9.89	-2.86			

Raw data: KLEMS
All the numbers are in percentages.

Dual Measure of TFP

In this subsection, I show that the dual measure of TFP tracks the primal measure well, which is consistent with the perfect competition assumption.

In the previous subsection, it is assumed that $s_{st}^L + s_{st}^K = 1$. One implication of this assumption is that the market is perfectly competitive: the labor share and capital share adds up to one, so that there is no profit. The concern then is that this assumption is too strong. A valid suspicion is that the decline in the measured TFP in expanding sectors may not reflect the drop of the productivity, but merely a drop of the markup if the market is not perfectly competitive.

According to Hsieh 2002,[6] with the assumption that the market is perfectly competitive, there exists an identity:[7]

$$\underbrace{\hat{Y}_{st} - s_{st}^K \hat{K} - s_{st}^L \hat{L}_{st}}_{\text{Primal: } \hat{A}_{st}^P} = \underbrace{s_{st}^K \hat{r}_{st} + s_{st}^L \hat{w}_{st}}_{\text{Dual: } \hat{A}_{st}^D} \tag{2.1}$$

The left-hand side of equation 2.1 is the primal measure, which in principle is the measure used in KLEMS. The right-hand side of equation 2.1 is the dual measure, $\hat{r}_{st}$ is the growth rate of the rental price of capital, and $\hat{w}_{st}$ is the growth rate of wage. s_{st}^K and s_{st}^L are respectively the capital share and the labor share.

If the market is not perfectly competitive, the output should be divided into factor shares

[6]Hsieh 2002 shows that in the cases of Singapore and Taiwan, the dual measure does not matches the primal measure well. He does not question the validity of the specification of the assumption of market condition, but instead questions the quality of national account. In the case of European data, however, the data quality is much less of a concern.

[7]The derivation of the equation can be found in Appendix 3.7.

and profit:

$$Y_{st} = r_{st}K_{st} + w_{st}L_{st} + \pi_{st} \tag{2.2}$$

where π_{st} is the profit of sector s at time t.

Then we have a similar expression as in equation 2.1:

$$\underbrace{\hat{Y}_{st} - (1 - s^L_{st})\hat{K}_{st} - s^L_{st}\hat{L}_{st}}_{\text{Primal: } \hat{A}^P_{st}} = \underbrace{(1 - s^L_{st})\hat{r}_{st} + s^L_{st}\hat{w}_{st}}_{\text{Dual: } \hat{A}^D_{st}} + s^\pi_{st}(\hat{s}^\pi_{st} - \hat{s}^K_{st}) \tag{2.3}$$

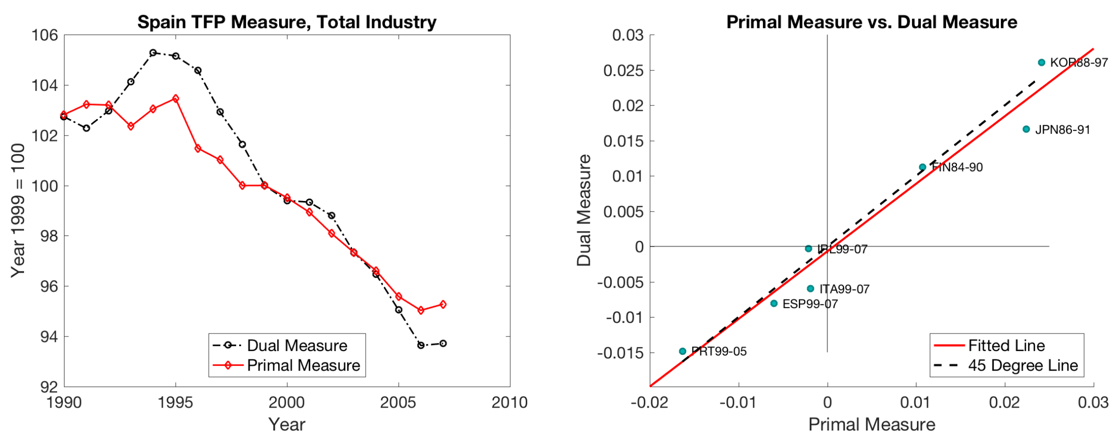
Equation 2.3 shows that if we still mistakenly assume that the labor share and the capital share sums up to one if the truth is not, the primal measure would exceed the dual measure by $s^\pi_{st}(\hat{s}^\pi_{st} - \hat{s}^K_{st})$.

In Figure 2.3a, I show that the dual measure and the primal measure of the TFP of Spain are indeed very close to each other. In Figure 2.3b, I present the scatter plot of the primal measure versus the dual measure for the seven countries/periods explored in the previous subsection. Every dot represents the annualized TFP growth for that country during the period associated. The red solid line is the linearly fitted line of the scatter plot, and the black dashed line is the 45-degree line. The closeness of the two lines indicates that the two measures matches each other very well.

A more specific way to read Figure 2.3 is that the term $s^\pi_{st}(\hat{s}^\pi_{st} - \hat{s}^K_{st})$ in equation 2.3 is small. And Figure 2.4 proves it is because the profit share s^π_{st} is small, which further implies that the competitive market assumption is a reasonable one. Indeed, if $s^\pi_{st}(\hat{s}^\pi_{st} - \hat{s}^K_{st})$

is small is due to the fact that the difference between the growth rate of capital share and that of profit share $(\hat{s}^{\pi}_{st} - \hat{s}^{K}_{st})$ is small, then we would expect the labor share to increase. The reason is that attributing the measured TFP decline to markup drop would require profit share to decrease as well. Then the capital share would need to decline at about the same rate. The combination of the decline in capital share and the decline in profit share requires the labor share to increase. However, Figure 2.4 shows that the labor share is actually decreasing in Spain.

Figure 2.3: Primal Measure and Dual Measure



(a) (b)

Raw data: KLEMS
1999 TFP is normalized to 100
Next to every dot there are three letters and numbers; the three letters stands for countries, and the numbers are the starting and end years: PRT99-05 (Portugal 1999 -2005), ESP99-07(Spain 1999 - 2007), ITA99-07 (Italy 1999 - 2007), IRL99-07(Ireland 1999 - 2007), FIN84-90 (Finland 1984 - 1990), JPN86-91 (Japan 1986 - 1991), KOR88-97 (Korea 1988 - 1997)
Portugal data is from 1999 - 2005 is because of data availability in the the release of the 2009 version of KLEMS.

Figure 2.4: Labor Share of Spain

Raw data: KLEMS

2.3 Firm-level Evidence on TFP Decline

In this section, I show that the trend of TFP observed in aggregate data also exists in the firm-level data using very different estimation methods. Moreover, the firm-level data suggests that the capital misallocation channel cannot explain the TFP drop, but the labor-quality mismeasurement channel can.

Firm-level data used in this section are the AMADEUS firm-level panel data of Spain from 1999 to 2007. I describe how I construct the dataset in Appendix 3.7.

Then I merge the price data to the firm-level data. The ideal price data would be firm-level producer price. However, it is not available. The price data used in the paper are the two-digit sectoral level data of nominal value added and intermediate inputs from KLEMS ISIC 3. 2009 release. The price data of fixed assets are quasi two-digit sectoral level data from the same source. Some two-digit sectors share the same price index of fixed assets. For example, food/beverage and tobacco are two different two-digit sectors, but they have the identical price index of fixed assets.

Capital Misallocation

In this subsection, I prove that the capital misallocation channel is not the channel of the first-order importance to explain the TFP drop. More specifically, I show that the growth of the dispersion of the marginal revenue product of capital (MRPK) is higher in non-expanding sectors relative to expanding sectors.

The calculation of the MRPK follows Chang-Tai Hsieh 2009 and Gopinath et al. Forthcoming. The production function is assumed to be Cobb-Douglas: $Y_{ist} = A_{ist}K_{ist}^{\alpha_s}L_{ist}^{\beta_s}$. Here it is not necessary that the production function is constant return to scale, but it is assumed to be time invariant. The MRPK is defined as follows:

$$\mathrm{MRPK}_{ist} :\equiv \alpha_s\mu_s\frac{P_{ist}Y_{ist}}{K_{ist}} \tag{2.4}$$

where μ_s is the time invariant mark-up of sector s, P_{ist} is the price of the output of firm i in sector s at time t. If it is perfect competition, then $\mu_s = 1$. If it is monopolistic competition with a CES aggregator, then $\mu_s = \frac{\sigma_s}{\sigma_s - 1}$, where σ_s is the time invariant elasticity of substitution.

$P_{ist}Y_{ist}$ is the nominal value-added of the firm calculated as the difference between the operational income and the material cost. K_{ist} here is defined as the fixed asset deflated by the capital price from KLEMS, and L_{ist} is the number of people employed.

The dispersion of the MRPK of sector s is defined as the standard deviation of the log MRPK:

$$\text{Dispersion of MRPK}_{st} :\equiv std(\ln(\text{MRPK}_{ist})) \tag{2.5}$$

Here I do not have to assign the values to α_s, β_s and μ_s since after taking the log value of the MRPK, the constant term across all firms within a sector becomes additive. So it does not add to the variation of the log value of the MRPK.

Figure 2.5 plots the evolution of the dispersion of the MRPK in both the manufacturing sector and the construction sector. Both curves have an upward trend, but the manufacturing sector clearly has a higher growth of the dispersion of the MRPK than that of the construction sector.

According to Chang-Tai Hsieh 2009, the increasing dispersion of the MRPK is an indicator of the worsening situation of capital misallocation. The idea is that without distortion on capital allocation the marginal productivity of all firms should be equalized, and there would be no capital misallocation. Thus, the dispersion of the MRPK should always be zero.[8]

If we focus on just one sector, it is tempting to draw the conclusion that the capital misallocation is increasing within that sector. However, if the capital misallocation channel is really the main reason TFP drops, we should expect the sector with more TFP drop to experience a higher growth of the dispersion of the MRPK. However, we observe the opposite in Figure 2.5.

The main message in this subsection is that the capital misallocation cannot be the main driver of the TFP drop.

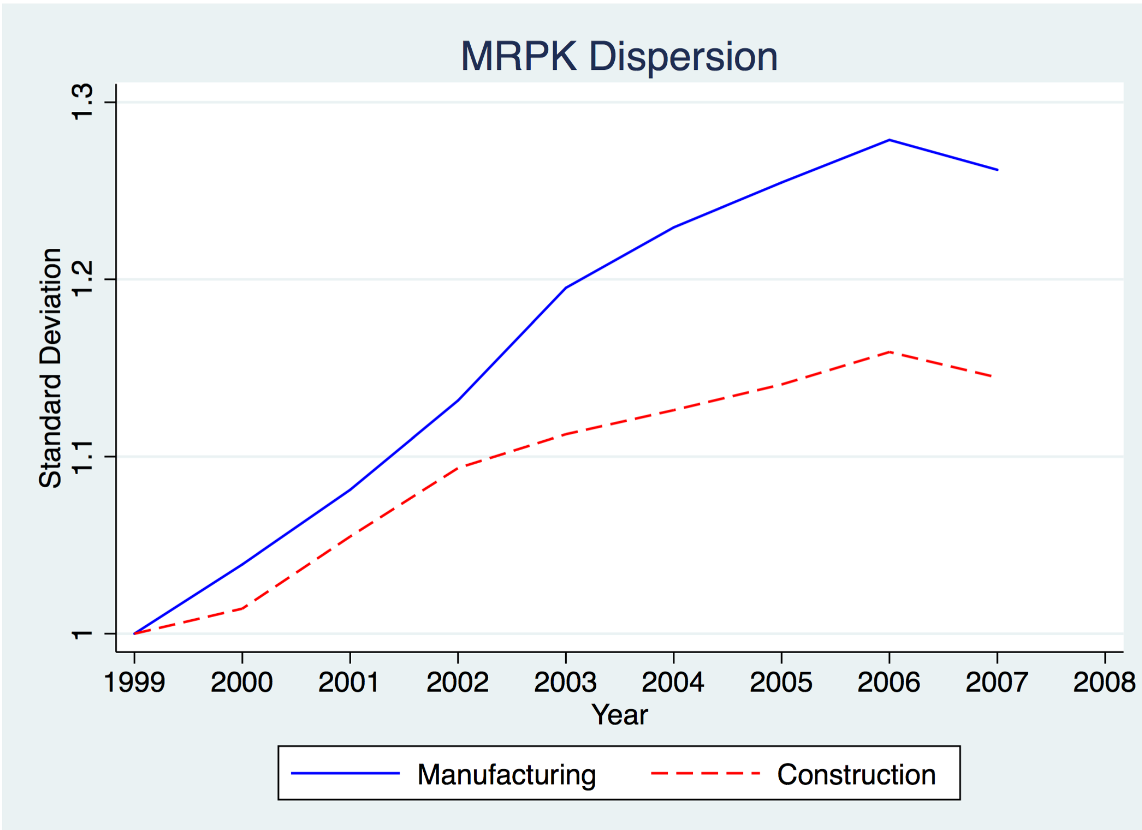
Time Series Trend of TFP

In this subsection, I present the time series trend TFP with firm-level data. It also shows that average TFP declines much more in expanding sectors than in non-expanding sectors.

This paper estimates the firm-level TFP using different methodologies, which gives very similar results. More specifically, I employed the Ackerberg, Caves, and Frazer 2015 extension of Levinsohn and Petrin 2003 and De Loecker 2011 methodologies. Olley and Pakes 1996 is often cited side by side with Levinsohn and Petrin 2003. Both papers try to solve the potential endogeneity problem caused by the correlation between the unobserved productivity and factor inputs. Olley and Pakes 1996 assumes the investment contains the information on productivity, while Levinsohn and Petrin 2003 assumes the intermediate

[8] Even if the dispersion of the MRPK is not necessarily a good measure of capital misallocation, as argued by **DeLoeckeretal2014** and Bils, Klenow, and Ruane 2017, one still needs to reject capital misallocation as the main explanation for the TFP decline, since almost all the papers favoring the argument of capital misallocation follow Chang-Tai Hsieh 2009.

Figure 2.5: MRPK Dispersion Comparison



Raw data: Amadeus Spain

inputs contain information on productivity. Intermediate inputs could be better than investment as a proxy for productivity due to the lumpiness of the investment. As pointed out by Ackerberg, Caves, and Frazer 2015, treating labor as a free variable in the first stage of estimation is problematic because productivity under some data generating processes. To deal with the concern that the difference between the firm-level price and sectoral-level price might bias the estimation result, I also include De Loecker 2011 methodology.

The estimation results in Tables 2.3 demonstrates two things: (1) different estimation methods reveal similar results, and (2) constant return to scale may be a good approximation. Table 2.3 shows the coefficient of production function. The upper panel represents the point estimations, while the lower panel shows the corresponding standard errors. The left panel is the estimation with the full sample, while the middle panel is the estimation of the half sample. In the half sample, I exclude the firms with less than or equal to five observations. So, in the half sample, all firms exist in at least two of the vintage discs. The right panel is the estimation with the subsample of only stayers. Comparison across samples shows that the full sample has a higher labor share and a lower capital share relative to the half sample and subsample of stayers. The production function in the full sample is closer to constant return to scale.

Figure 2.6 shows a strikingly difference between the trends of the manufacturing sector and the construction sector: the mean of the log value of TFP of the former declines little compared to that of the latter. More specifically, Figure 2.6 shows the weighted and unweighted log value of TFP in the manufacturing and construction sectors, aggregated from the firm-level TFP measured by the methodologies in Levinsohn and Petrin 2003 and De Loecker 2011 with the full sample of firms. Horizontally, the first row plots the unweighted mean, valued-added-weighted mean, and labor-weighted mean of the log value TFP of the manufacturing sector using the De Loecker and the Levinsohn-Petrin estimators. The second row plots the same trends in the construction sector. To make the comparison more clearer, the third row puts the valued-weighted mean of the log value of TFP of the two sectors in the same scale. Vertically, the left column and the right shows almost identical aggregate trends, although there is a slight difference in the point estimation of the coefficients of the production function. From 1999 to 2007, the average TFP of the manufacturing sector drops from 0.08 to 0.12 log points, depending on the aggregation weights. Although the decline trend seems similar in the construction sector, the magnitude is much bigger: the TFP drop is from 0.45 to 0.5 log points. Figure 2.6 further reveals that the value-weighted mean of the log value of TFP is always above the unweighted mean, which implies that the higher value-added firms have higher TFP.

One interesting point in Figure 2.6 is the discrepancy between the firm-level TFP trend and the KLEMS measure. From the firm-level TFP measure, we observe a more profound TFP drop. This is because the KLEMS measure partially controls the labor quality, while the firm-level TFP measure does not control for it at all. I will discuss this issue in detail in the next section.

Figure 2.7 and Figure 2.8 are copies of Figure 2.6 with different subsamples instead of the full sample. The divergence of the trends for TFP between the manufacturing sector and the construction sector is still there, with a sharp drop in the latter and even a slight increase in the former. The magnitude of the drop in the construction sector is much smaller though in Figure 2.7 and Figure 2.8 compared to that in Figure 2.6, about 0.25 and 0.15, respectively, against about 0.5 measured in log points. This comparison reflects that younger firms may contributes significantly to the measured TFP drop.

Figure 2.9 is a zoom-in graph of Figures 2.6, 2.7 and 2.8, in the sense that the distributions of the log value of TFP of two end years are plotted. The mean of the 1999 distribution of the log value of TFP is normalized to zero. Horizontally, the first row shows the result of the full sample, the second row that of the half sample, and the third row that of the subsample of only stayers. Vertically, the first column is the result of distribution of manufacturing sector and the second column that of the construction sector.

The pattern that has been observed in Figures 2.6, 2.7 and 2.8 can also be observed in Figure 2.9 by how much the 2007 log TFP distribution changes relative to the 1999 one. In the left column, the two distribution overlaps with each other quite well, meaning the aggregate TFP is not that different between 1999 and 2007 in the manufacturing sector. In the right column, there is a clear move of the distribution to the left, implying a significant decline of TFP in the construction sector during the same time period.

A new stylized facts that cannot be observed in the aggregate time series is the dispersion of the TFP. The first row is the distribution based on the full sample. The right tail of the construction sector extends to the right only slightly, while it stays almost the same for the manufacturing sector. However, in the construction sector, the left extension of the left tail is much more pronounced compared to that of the manufacturing sector. The extension of the left tail can be interpreted as the the entry of the new firms that could not enter the production procedure without the sector expansion. There are proportionally more firms like this in the construction sector than in the manufacturing sector because the expansion scale is very different in the two sectors, as shown in the first section. The second row and the third row are the distribution based on the half sample and sub sample of only stayers. The tails of the distributions do not seem too different between 1999 and 2007.

Table 2.3: Production Function Coefficients

	Full Sample				**Half Sample**				**Subsample(Stayers)**			
Methods	**DL**		**LP**		**DL**		**LP**		**DL**		**LP**	
Sectors	α_l	α_k	α_l	α_k	α_l	α_k	α_l	α_k	α_l	α_k	α_l	α_k
Manufacturing	0.794	0.200	0.821	0.208	0.688	0.225	0.691	0.226	0.678	0.237	0.680	0.239
Construction	0.801	0.195	0.782	0.183	0.618	0.179	0.617	0.172	0.622	0.185	0.615	0.171
Real Estate	0.832	0.203	0.745	0.179	0.575	0.187	0.550	0.175	0.575	0.175	0.541	0.185

Standard Errors

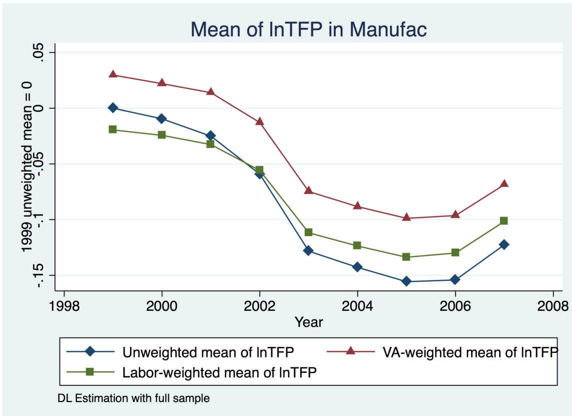
	SE α_l	SE α_k	SE α_l	SE α_k	SE α_l	SE α_k	SE α_l	SE α_k	SE α_l	SE α_k	SE α_l	SE α_k
Manufacturing	0.00027	0.00002	0.00006	0.00004	0.00009	0.00002	0.00007	0.00001	0.00359	0.00980	0.00013	0.00001
Construction	0.00157	0.00036	0.00083	0.00272	0.00021	0.00018	0.00048	0.00015	0.00216	0.00576	0.00185	0.00242
Real Estate	0.00052	0.00002	0.00033	0.00023	0.01248	0.00717	0.00003	0.00004	0.01927	0.00715	0.00045	0.00028

Raw data: Amadeus Spain

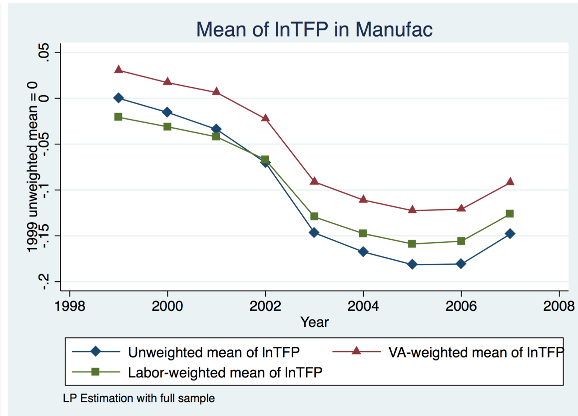
DL means the estimation method is De Loecker 2011; LP means the estimation method is Levinsohn and Petrin 2003

Full sample is the sample with all firms; Half sample is the sub sample with observations more than 5; Sub sample (stayers) is the sub sample with firms that have observations every year.

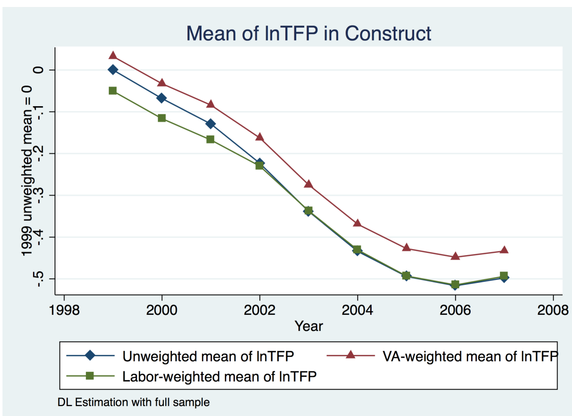
Figure 2.6: Mean lnTFP Trend Full Sample



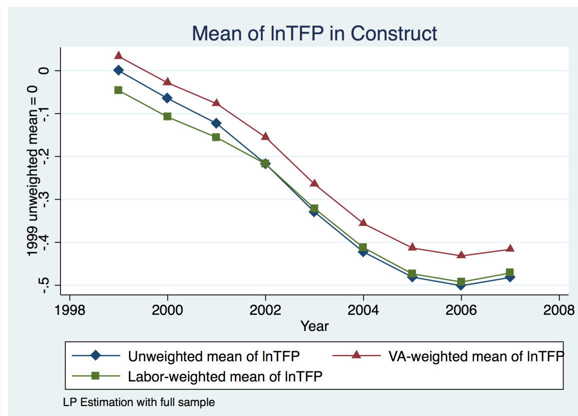
(a)



(b)



(c)



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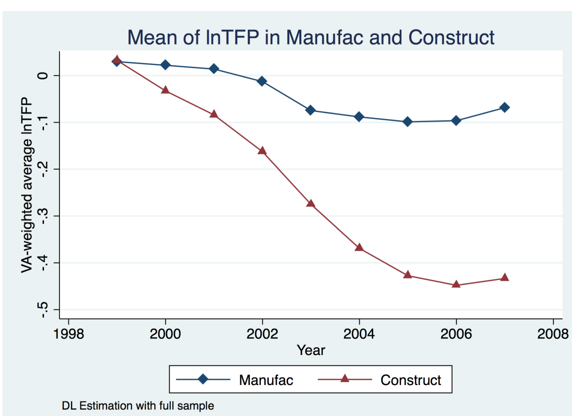
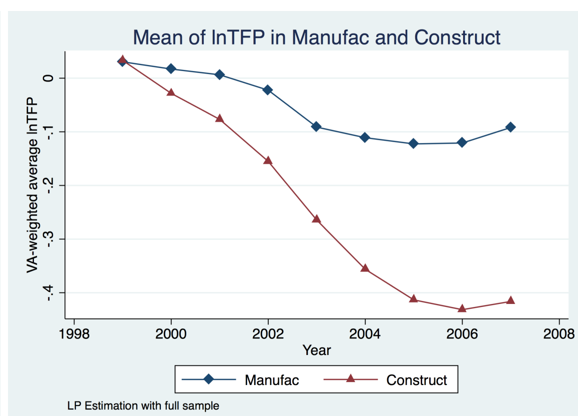


(e)



(f)

Raw data: Amadeus Spain, Full Sample

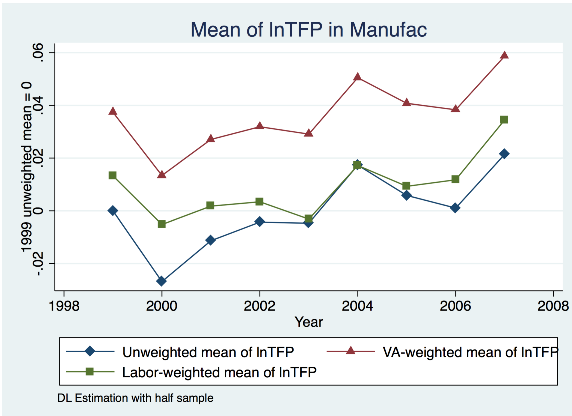
The left three graphs use the De Loecker estimator, the right three graphs use the Levinsohn and Petrin estimator.

The mean is normalized such that in year 1999, unweighted mean of lnTFP is zero.

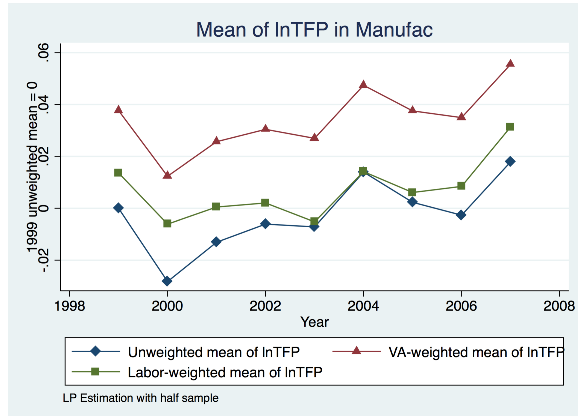
The trend of graph is comparable across all subgraphs. But the levels of lnTFP is comparable only within the same sector and with same estimation.

In sub-graph 2.4e and 2.4f, I put the va-weighted mean of lnTFP of both manufacturing sector and construction sector together for a more direct comparison.

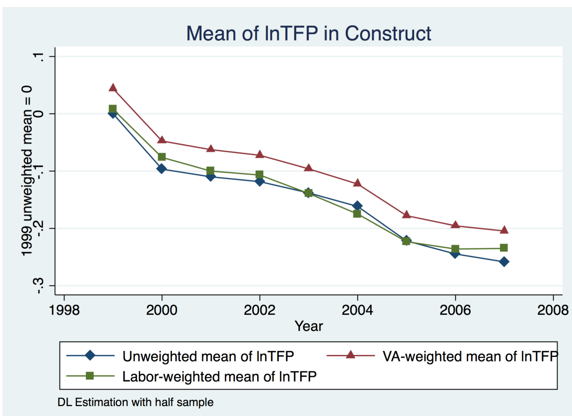
Figure 2.7: Mean lnTFP Trend Half Permanent Sample



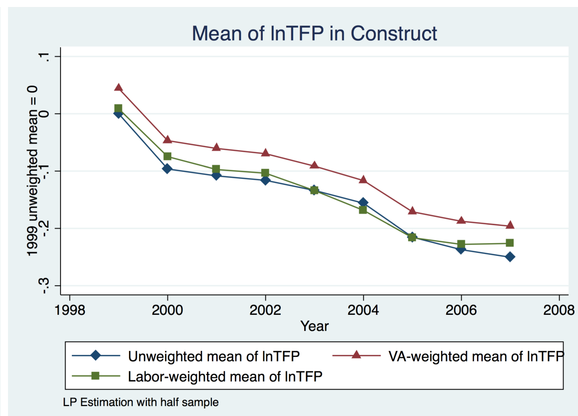
(a)



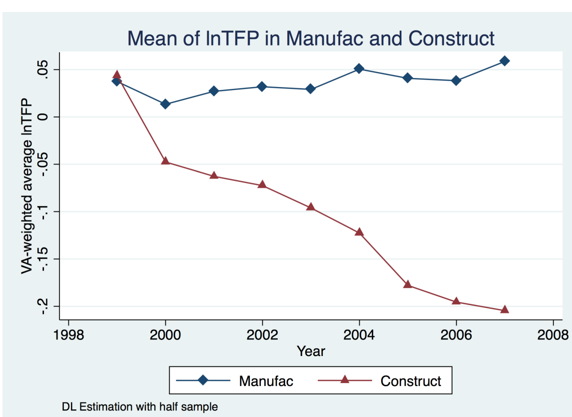
(b)



(c)



(d)



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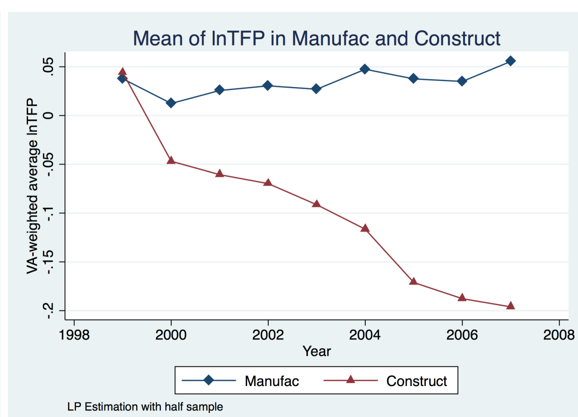


(f)

Raw data: Amadeus Spain, Half Sample (obs more than 5)

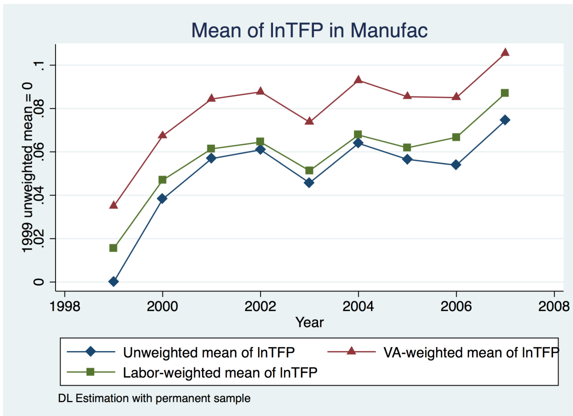
The left three graphs use the De Loecker estimator, the right three graphs use the Levinsohn and Petrin estimator.

The mean is normalized such that in year 1999, unweighted mean of lnTFP is zero.

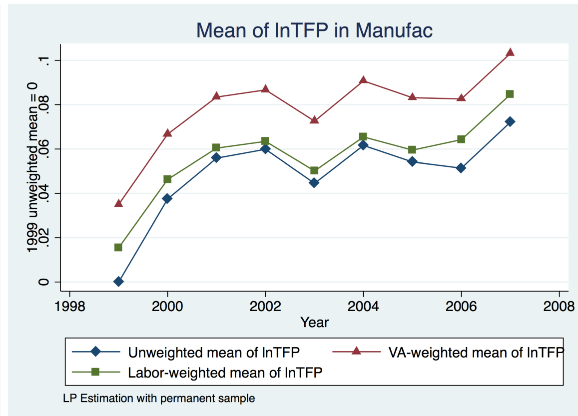
The trend of graph is comparable across all subgraphs. But the levels of lnTFP is comparable only within the same sector and with same estimation.

In sub-graph 2.4e and 2.4f, I put the va-weighted mean of lnTFP of both manufacturing sector and construction sector together for a more direct comparison.

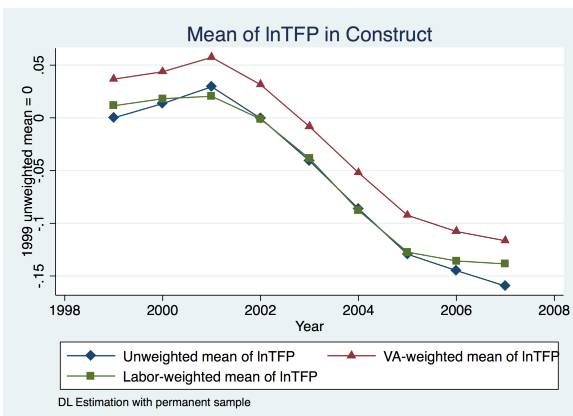
Figure 2.8: Mean lnTFP Trend Permanent Sample



(a)



(b)



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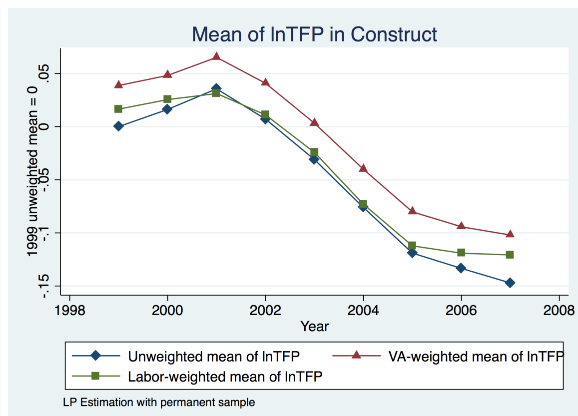

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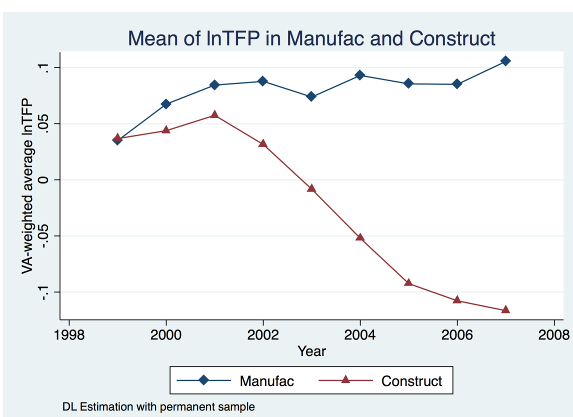

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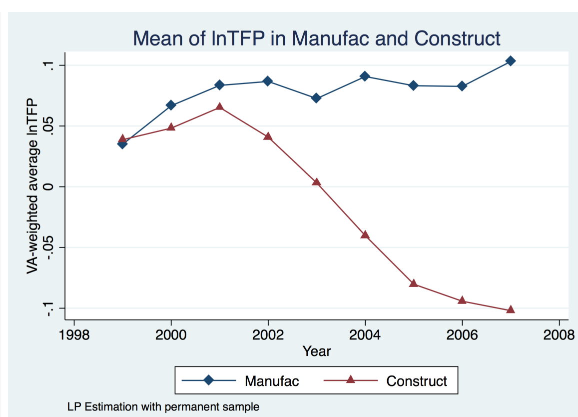


(f)

Raw data: Amadeus Spain, Permanent Sample (has obs every year)

The left three graphs use the De Loecker estimator, the right three graphs use the Levinsohn and Petrin estimator.

The mean is normalized such that in year 1999, unweighted mean of lnTFP is zero.

The trend of graph is comparable across all subgraphs. But the levels of lnTFP is comparable only within the same sector and with same estimation.

In sub-graph 2.4e and 2.4f, I put the va-weighted mean of lnTFP of both manufacturing sector and construction sector together for a more direct comparison.

TFP Growth Decomposition

In this subsection, I present another piece of evidence that the capital misallocation channle cannot be the main reason TFP drops, but th labor-quality mismeasurement channel can be.

The sectoral average TFP growth can be decomposed into five components: within-firm term, between-firm term, cross term, entry term and exit term. The first three components come from the firms that always stay in the sample (sub sample of stayers), the entry term is from the newly incoming firms, and the exit term is from the firms that exit the sample. The decomposition result shows that the between-firm component is almost negligible. This means that capital misallocation is not important in explaining the TFP drop within the subsample of stayers. The importance of the within-firm component implies consistency with the mismeasurement channel.

Following Alvarez, Chen, and Li 2017, the change of the weighted average of the log value of TFP can be decomposed to five terms, as follows:

$$\Delta a_{st}^{total} \equiv \bar{a}_{st} - \bar{a}_{sr}$$

$$\equiv \sum_{i=1}^{N_{st}} \frac{Y_{ist}}{\mathrm{Y}_{st}} a_{ist} - \sum_{i=1}^{N_{sr}} \frac{Y_{isr}}{\mathrm{Y}_{sr}} a_{isr}$$

$$= \underbrace{\frac{\mathrm{Y}_{sr}^{stay}}{\mathrm{Y}_{sr}} \sum_{i \in stay} \frac{Y_{isr}}{\mathrm{Y}_{sr}^{stay}} (a_{ist} - a_{isr})}_{\Delta a_{st}^{Within}} + \underbrace{\frac{\mathrm{Y}_{sr}^{stay}}{\mathrm{Y}_{sr}} \sum_{i \in stay} \left[\left(\frac{\mathrm{Y}_{st}^{stay}}{\mathrm{Y}_{st}} / \frac{\mathrm{Y}_{sr}^{stay}}{\mathrm{Y}_{sr}} \right) \frac{Y_{ist}}{\mathrm{Y}_{st}^{stay}} - \frac{Y_{isr}}{\mathrm{Y}_{sr}^{stay}} \right] (a_{isr} - \bar{a}_{sr})}_{\Delta a_{st}^{Between}}$$

$$+ \underbrace{\sum_{i \in stay} \left(\frac{Y_{ist}}{\mathrm{Y}_{st}} - \frac{Y_{isr}}{\mathrm{Y}_{sr}} \right) (a_{ist} - a_{isr})}_{\Delta a_{st}^{Cross}} + \underbrace{\sum_{i \in enter} \frac{Y_{ist}}{\mathrm{Y}_{st}} (a_{ist} - \bar{a}_{sr})}_{\Delta a_{st}^{Entry}} - \underbrace{\sum_{i \in exit} \frac{Y_{isr}}{\mathrm{Y}_{sr}} (a_{isr} - \bar{a}_{sr})}_{\Delta a_{st}^{Exit}} \tag{2.6}$$

where

$$\mathrm{Y}_{st} = \sum_{i=1}^{N_{st}} Y_{ist};$$

$$\mathrm{Y}_{sr} = \sum_{i=1}^{N_{sr}} Y_{isr};$$

$$\mathrm{Y}_{st}^{stay} = \sum_{i \in stay} Y_{ist};$$

$$\mathrm{Y}_{sr}^{stay} = \sum_{i \in stay} Y_{isr};$$

where $a = \ln A$, Y_{st} is the total real value added in year t of sector s, and Y_{sr} is its counterpart in reference year r. N_{st} is the total number of firms. $stay$ is the subset of firms that exist both in year t and year r. $exit$ is the subset of firms that exist in the reference year r but do not in year t, (i.e., firms that exit the sample). $enter$ is the subset of firms that do not exist in the reference year r but do in year t, (i.e., firms that enter the sample). Y^{stay} is the total real value added of the subset of firms in $stay$. Technically speaking, equation 2.6 has one more term: $\bar{a}_{sr}\big[\sum_{i \in stay}(\frac{Y_{ist}}{\mathrm{Y}_{st}} - \frac{Y_{isr}}{\mathrm{Y}_{sr}}) + \sum_{i \in enter}\frac{Y_{ist}}{\mathrm{Y}_{st}} + \sum_{i \in exit}\frac{Y_{isr}}{\mathrm{Y}_{sr}}\big]$, but since we can normalize $\bar{a}_{sr}$ to be zero, it is ignored.

Then the change of the weighted average of log TFP of year t in sector s relative to the reference year r can be decomposed into five parts: "within," "between," "cross," "entry" and "exit." The "within" term keeps the weight of the reference year unchanged but varies the TFP of individual firms, so it indeed measures the contribution of the log TFP change within the same firms that exist both in year t and in reference year r. If we further assume that on average a firm does not have a TFP drop, then the "within" term measures the TFP change stemming from the mismeasurement of the labor quality of the firms that survive.

The "between" term keeps the TFP of firms unchanged but varies the weight of individual firms. So it indeed measures the relative firm size change due to the reallocation of the resource. If $\Delta a_{st}^{Between} > 0$, it means that high productive firms become larger in size. If $\Delta a_{st}^{Between} < 0$, it means that low productive firms expand more, which means the allocation efficiency worsens. If $\Delta a_{st}^{Between} \approx 0$, it implies that the misallocation channel may not be important, at least in the subset of $stay$ firms.

The "cross" term captures the correlation between the change of TFP and change of the size. If $\Delta a_{st}^{Crosss} > 0$, it means that when a firm grows in size, it also grows in productivity. If $\Delta a_{st}^{Crosss} < 0$, it means that a firm expands in size but decreases in productivity.

The "entry" term measures the weighted average of the log TFP of firms that newly enter the market in year t but do not exit in reference year r. So this term contains the change both from the misallocation channel and from the mismeasurement channel.

The "exit" term measures the weighted average of the log TFP of firms that exist in reference year r but do not exist anymore in year t.

Figure 2.10 plots graphically the decomposition based on equation 2.6 between year 2007 and reference year 1999, for both the manufacturing sector and the construction sector. The navy bars, standing for the total log TFP change in both sectors, echoes the observation in Figure 2.6: a small TFP drop is observed in the construction sector while a big TFP drop is observed in the construction sector. The "within" part is strikingly different in the two subfigures; while it is slightly positive in the manufacturing sector, it accounts for almost one-third of the TFP drop in the construction sector. The "between" term is small in both sectors. This stark contrast between the two sectors implies that at least in the subsample of stayers, the misallocation cannot be the dominant channel.

It is also observed that the "entry" bar is as important as the "total" bar. This means that the group of newly entering firms has a measured TFP that is much lower than the weighted average of the reference year. However, this bar contains both the misallocation channel and the mismeasurement channel. Therefore, we need a model to tear apart these two channels within the “entry” group.

2.4 Evidence of Labor Quality from Worker-Firm Matched Data

In this section, I present two results using worker-firm matched data from the Structure of Earnings Survey (SES) of Eurostat: first, the labor quality control with only limited observable characteristics fails to capture a big share of the wage variation; second, the labor quality deteriorates in expanding sectors but not in non-expanding sectors.

The SES data are obtained by a two-stage random sampling approach of enterprises or local units (first-stage) and employees (second stage). The frequency of the survey is every four years. The data used in this paper are from the surveys of 2002 and 2006.

There are a few technical complications. First, although the anonymization procedure used to protect the privacy of firms and workers might change the precision of the survey, the statistics of the data shows that such modification has a statistically insignificant effect on the information of the survey. The natural step of anonymization is to replace names of firms and workers by codes which are not identifiable. This step does not change the real content of the survey. However, even after this step, firms and workers are still subject to the risk of ”spontaneous identification” due to the information revealed by their characteristics. So a further anonymization procedure is to make the characteristics of firms or workers a bit vaguer if there exists such a risk. For example, if in a certain area there is only one firm that employs more than 250 employees, then the size of that firm may be modified to more than 49 employees. Such changes only affect a very small group of observations.

Another technical complication is the consistency of the survey across years. The 2002 survey of Spain does not include local units of enterprises with fewer than 10 employees, but the 2006 survey does include those small local units. Therefore, to make the data comparable across years, I delete the workers working in the local units with fewer than 10 employees. This may cause an upward bias of the labor quality change in the expanding sector, and I will discuss it in the subsection 2.4.

Third, the randomization in selecting firms and workers and the anonymization procedure render the SES data to be cross-sectional for each survey. Alternatively speaking, the SES data has no panel feature, which leaves it inappropriate to run the two-way fixed-effect model as in Abowd and Kramarz 1999 and Card et al. 2016. However, I can still back out the distribution of the unobserved labor quality by running the regression of wage on firm fixed effect and observed labor quality. The potential assortative matching between firms and workers will result in a less dispersed residual wage compared to the dispersion of the unobserved labor quality. I will discuss in subsection 2.4 that this actually underestimates the importance of the unobserved labor quality. [9]

[9] Abowd and Kramarz 1999 and other following papers such as Card et al. 2016 usually show that there is very little correlation between the worker fixed effect and the firm fixed effect.

Insufficiency of the KLEMS' Control of Labor Quality

In this subsection, I argue that the labor quality control in the KLEMS dataset is limited and not sufficient to capture a big portion of the wage variation.

The evidence to support this argument comes from examining how much wage variation can be explained by the observed labor quality characteristics in the KLEMS dataset. More specifically, I investigate the R-square statistics of the regression of log wage on the observed labor quality characteristics in the KLEMS dataset. According to O'Mahony and Timmer 2009, the KLEMS dataset cross-classifies the labor force by gender, educational attainment and age into 18 categories (respectively, $2 \times 3 \times 3$ types). The SES worker-firm matched data have more detailed categorization of educational attainment and age (respectively, 6 types).

More specifically, I run the following regression for each year on the sectoral level and for the entire economy.

$$\ln(w_{jst}) = \alpha_{0st} + \text{gender}_{jst} + \text{education}_{jst} + \text{age}_{jst} + \varepsilon_{jst}, \tag{2.7}$$

where w_{jst} is the deflated wage bill of worker j in sector s at time t. The coefficients of the regression are omitted for the sake of simplicity.

Workers can be divided into two categories by gender, six by education, and six by age.

The result of the regression run in equation 2.7 is shown in Table 2.4. In the whole economy and in the manufacturing sector, about one-third of the wage variation can be explained by the observed labor quality characteristics used in KLEMS. In the construction sector, however, the same characteristics only account for about 20 percent of the wage variation.

The R-square statistics reveal two messages. First, generally speaking a majority of wage variation cannot be explained by the variation of the relatively easily observed labor characteristics such as gender, education attainment and age. Second, this unexplained wage variation problem is much worse in the construction sector. In order to capture the labor quality more precisely, more variables are needed.

Observed Labor Quality beyond KLEMS

In this subsection, I present evidence that labor quality deteriorates in expanding sectors compared to stable sectors beyond the dimensions controlled by KLEMS, (i.e., gender, age and education). One important dimension of workers' quality is the tenure, which depicts the length of the service in enterprise. The worker-firm matched data shows a significant difference of tenure length change between the construction sector and the manufacturing sector, both in average terms and for firm managers.

The average tenure in the construction sector has decreased by 2.5 percent, while that of the manufacturing sector has increased by 2.5 percent. One possible scenario is that people with low experience moved into the expanding construction sector, while no such labor movement into the non-expanding manufacturing sector.

A 5 percent difference in tenure growth might not seem large, but we have to take into account the following issues. First, it is just the growth difference from 2002 to 2006.

Table 2.4: Regression of ln(wage) on Observed Individual Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	2002			2006		
	All Sectors	Manufac.	Construc.	All Sectors	Manufac.	Construc.
	b/se	b/se	b/se	b/se	b/se	b/se
Gender F	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Gender M	0.243***	0.270***	0.199***	0.222***	0.263***	0.173***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
educ 1	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
educ 2	0.058***	0.038***	0.034***	0.034***	0.026***	0.015*
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
educ 3	0.274***	0.258***	0.163***	0.221***	0.214***	0.143***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
educ 4	0.356***	0.335***	0.176***	0.281***	0.286***	0.160***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
educ 5	0.666***	0.658***	0.556***	0.599***	0.561***	0.482***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
educ 6	0.775***	1.000***		0.650***	0.716***	0.285
	(0.02)	(0.04)		(0.01)	(0.04)	(0.17)
age 14-19	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
age 20-29	0.123***	0.159***	0.108***	0.096***	0.164***	0.076***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
age 30-39	0.319***	0.322***	0.218***	0.250***	0.298***	0.159***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
age 40-49	0.478***	0.494***	0.293***	0.382***	0.431***	0.221***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
age 50-59	0.573***	0.636***	0.363***	0.480***	0.557***	0.293***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
age 60+	0.531***	0.613***	0.380***	0.501***	0.578***	0.367***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.02)	(0.02)
Constant	1.270***	1.271***	1.392***	1.387***	1.350***	1.514***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Adj.R-sqr	0.344	0.365	0.198	0.328	0.334	0.198
Obs	216400	83808	15548	219723	77381	16641

Raw data from Structure of Earnings Survey - Eurostat

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Under a simplistic assumption that the growth rate is constant from 1999 to 2007, there would be a 10 percent difference in tenure growth between two sectors. Second, deletion of the local units with fewer than 10 employees may contribute to the underestimation of the difference of the growth rate of the tenure. The exclusion of of those small firms also excluds newly incoming labor. Since the expanding sectors have more such small firms and probably more unexperienced incoming workers, the difference in the growth rate of tenure could potentially be bigger.

The tenure of certain important occupations, such as managers, is arguably more important than just the average tenure, as it may reflect how much they know about managing the firm. The average tenure of the firm managers[10] in the construction sector has dropped from 8.94 years to 6.42 years from 2002 to 2006, which is a 28 percent decrease. However, the average tenure of the firm managers in the manufacturing sector has increased from 11.69 to 14.11 years during the same period of time, which is a 21 percent increase.

One concern of the evidence drawn from tenure length would be the age variation has almost captured all the tenure variation. However, the correlation between the age groups and the tenure groups shows that the age group variation does not capture all the variation in tenure group variation. Using the tenure group definition in the first column in Table 2.5, the SES data show that correlation between age and tenure is only 0.52 in all sectors, 0.32 in the construction sector and 0.61 in the manufacturing sector. This correlation is not due to the ad hoc definition of the tenure group. Using a different tenure group definition shown

[10] In the occupation classification, the firm managers are coded as 12 "corporate managers" and 13 "managers of small enterprises."

in the second column of Table 2.5, the correlation between age group and tenure group is 0.53 in all sectors, 0.34 in the construction sector and 0.62 in the manufacturing sector. If we consider yet another definition of tenure group as in column 3 of 2.5, the correlation between age group and tenure group is 0.53 in all sectors, 0.34 in the construction sector and 0.61 in the manufacturing sector. The message is that although there is positive correlation between tenure and age, the correlation is not 1. It means the tenure variable does contain information that the age variable does not.

Table 2.5: Tenure Group and Age Group

Tenure Group 1	Tenure Group 2	Tenure Group 2	Age Group
< 10	< 5	< 3	< 20
$[10, 20)$	$[5, 15)$	$[3, 13)$	$[20, 30)$
$[20, 30)$	$[15, 25)$	$[13, 23)$	$[30, 40)$
$[30, 40)$	$[25, 35)$	$[23, 33)$	$[40, 50)$
$[40, 50)$	$[35, 45)$	$[33, 43)$	$[50, 60)$
≥ 50	≥ 45	≥ 43	≥ 60

The age group is from the SES-Eurostat data
Tenure group 1, tenure group 2 and tenure group 3 are by the author's definition.

Unobserved Labor Quality

In this subsection, I show how I back out the distribution of the unobserved labor quality using worker-firm matched data. Although the worker-firm matched data have more information than KLEMS to characterize labor quality such as tenure length, it is impossible to exhaust all the labor characteristics that are related to labor quality. Other labor quality dimensions, such as diligence, communication skills, etc., are hard to measure by the data.

To back out the total unobserved labor quality, I assume that the wage variation has three sources: the firm characteristics, the observed labor characteristics used by KLEMS and other dimensions of labor quality beyond KLEMS. The idea is that after running the regression of the wage on gender, education, age and firm fixed effect, the residual wage variation can be attributed to other dimensions of labor quality beyond KLEMS.

The specification of the regression is shown in equation 2.8.

$$\ln(w_{jst}) = \alpha_{i(j)st} + \text{gender}_{jst} + \text{education}_{jst} + \text{age}_{jst} + \varepsilon_{jst}, \tag{2.8}$$

where w_{jst} is the deflated wage bill of worker j in sector s at time t, $i(j)$ indicates the firm's identifier where worker j works; and $\alpha_{i(j)st}$ is the firm fixed effect.[11] The coefficients of the regression are omitted for the sake of simplicity.

The result of the regression is shown in Table 2.6. Compared to the result of the regression without firm fixed effect in Table 2.4, the adjusted R-square has increased from 20-40 percent to 60-70 percent.

The unexplained wage variation in equation 2.8 can be interpreted as the unobserved labor quality, but I have to deal with the following concerns. First, there is potential assortative matching between firms and workers. While assortative matching itself is an open

[11] Firm fixed effect can be identified since there are more than one workers in each firm. On average, there are 8.6 observations in each firm.

question,[12] this problem only makes firm fixed effects capture some labor characteristics. Alternatively speaking, the unobserved labor characteristics should probably capture wage variation larger than just 30 - 40 percent. Second, some labor search models predict that even without labor heterogeneity there should be wage variation because of the search friction, such as Mortensen 2005. But even that strand of literature does not exclude labor quality to explain the wage dispersion. Moreover, Hornstein, Krusell, and Violante 2011 shows that frictional wage dispersion can only explains a small part of the wage variation using quantitative model.

The distribution of the residual wage distribution can then be used in the calibration of the model.

[12] Abowd and Kramarz 1999 and Card et al. 2016 find there is very limited assortative matching, while Borovicková and Shimer 2017 argues significant assortative matching.

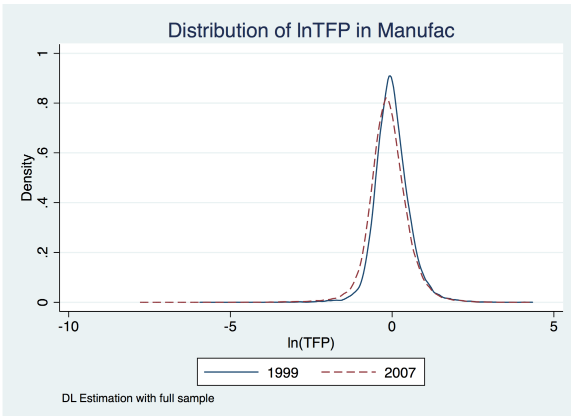
Table 2.6: Regression of ln(wage) on Observed Individual Characteristics and Firm Fixed Effect

	(1) 2002 All Sectors b/se	(2) Manufac. b/se	(3) Construc. b/se	(4) 2006 All Sectors b/se	(5) Manufac. b/se	(6) Construc. b/se
Gender F	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Gender M	0.182***	0.186***	0.197***	0.170***	0.190***	0.186***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)
age 14-19	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
age 20-29	0.070***	0.071***	0.068***	0.063***	0.112***	0.057**
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
age 30-39	0.221***	0.207***	0.156***	0.184***	0.218***	0.144***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
age 40-49	0.333***	0.332***	0.212***	0.278***	0.337***	0.183***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
age 50-59	0.383***	0.400***	0.263***	0.331***	0.401***	0.234***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
age 60+	0.391***	0.435***	0.276***	0.369***	0.431***	0.296***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)
educ 1	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
educ 2	0.045***	0.042***	0.055***	0.033***	0.044***	0.062***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
educ 3	0.136***	0.148***	0.112***	0.107***	0.131***	0.115***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
educ 4	0.174***	0.181***	0.107***	0.134***	0.163***	0.136***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
educ 5	0.435***	0.472***	0.402***	0.368***	0.409***	0.333***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
educ 6	0.600***	0.664***		0.501***	0.554***	0.034
	(0.03)	(0.06)		(0.02)	(0.07)	(0.23)
Constant	1.510***	1.531***	1.474***	1.587***	1.543***	1.536***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.03)
Adj.R-sqr	0.687	0.714	0.639	0.629	0.626	0.593
Obs	216400	83808	15548	219723	77381	16641

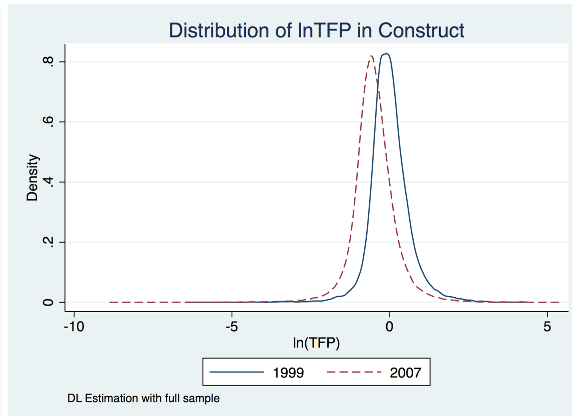
Raw data from Structure of Earnings Survey - Eurostat

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

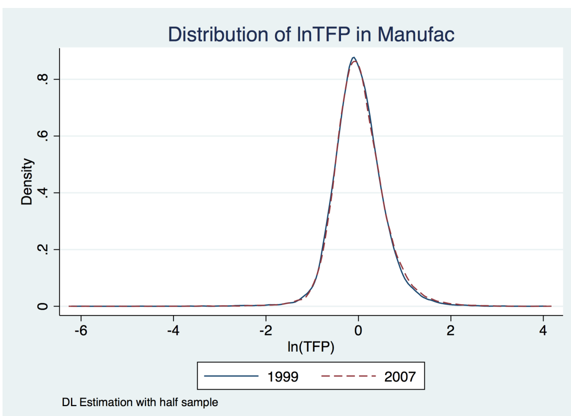
Figure 2.9: lnTFP Distribution



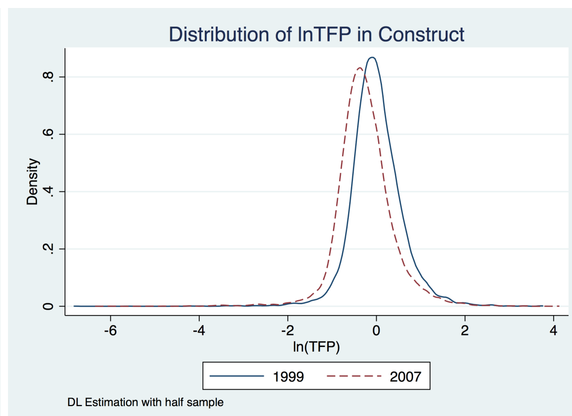
(a)



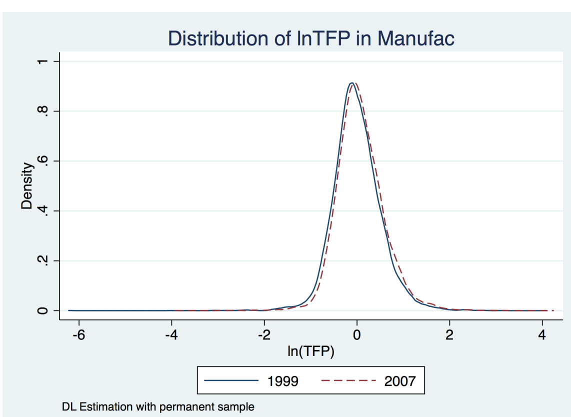
(b)



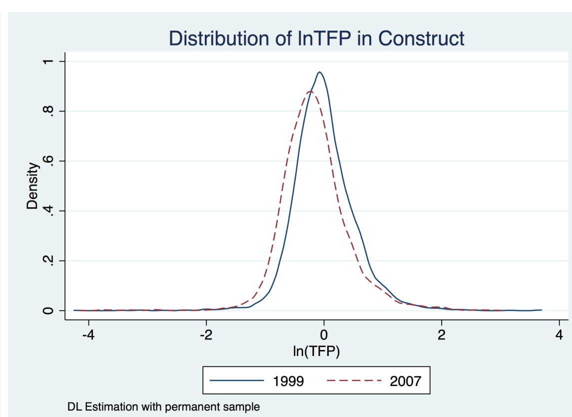
(c)



(d)



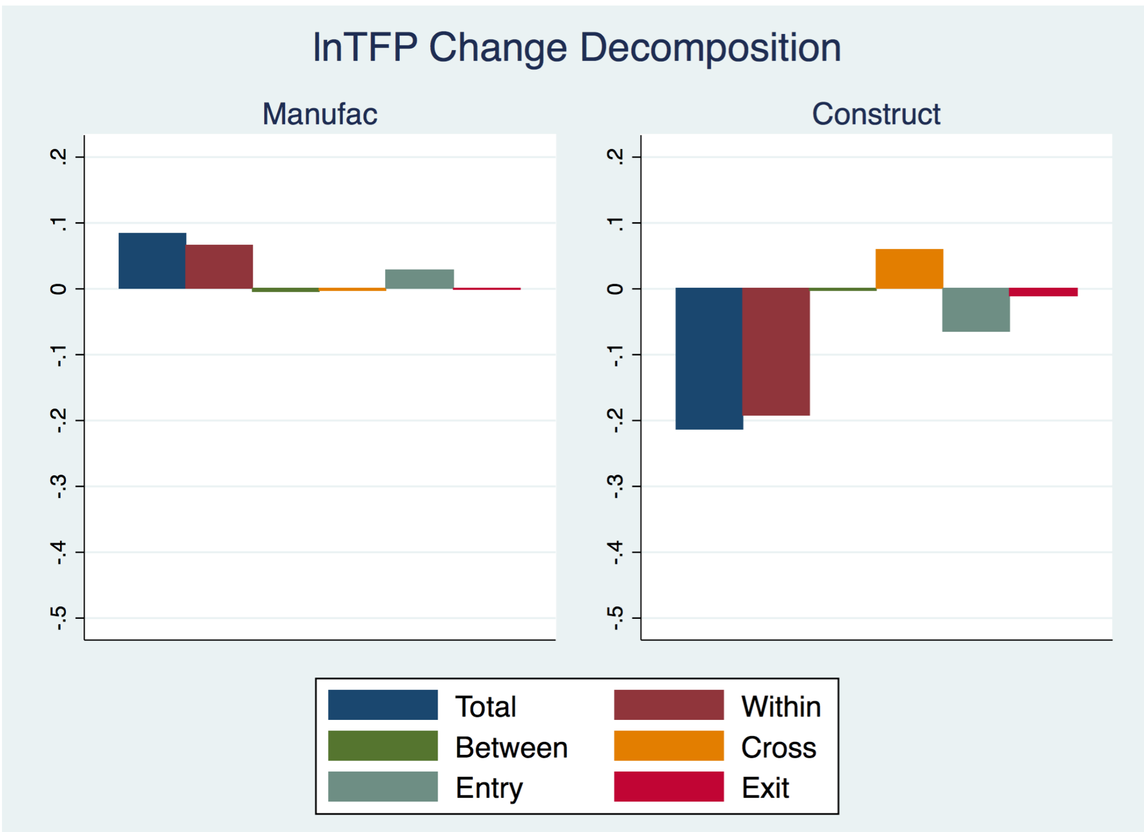
(e)



(f)

Source: Amadeus Spain
First row: full sample; second row: half sample; third row: subsample with stayers
TFP is the De Loecker estimator.
The mean is normalized such that in the year 1999, unweighted mean of lnTFP is zero.

Figure 2.10: Decomposition



Raw data: Amadeus Spain, full sample
$\Delta a_{st}^{total} = \Delta a_{st}^{Within} + \Delta a_{st}^{Between} + \Delta a_{st}^{Cross} + \Delta a_{st}^{Entry} + +\Delta a_{st}^{Exit}$ The full definition of the decomposition is in equation 2.6.

2.5 Model

This is an infinite horizon model that features both the misallocation and the mismeasurement channels. With the key distributions calibrated to micro data, the model predicts a much milder true TFP drop compared to the measured one.

The misallocation channel is built on Reis 2013, and the mismeasurement channel is built on Young 2014. The model has four types of agents: a household with heterogeneous workers, a tradable sector with a representative firm, a non-tradable sector with heterogeneous entrepreneurs, and a representative bank.

The mechanism of the model is as follows: a negative interest rate shock (Eurozone integration) enables the low-productivity firms in the expanding sector (the non-tradable sector) to enter the production by borrowing. This brings down the average productivity of this sector. Moreover, the borrowing cost for existing non-tradable firms is also lowered and allows them to borrow more; thus, the sector expands. The tradable sector is not affected by the shock since it is assumed that the tradable firms are far less financially constrained. Therefore, there is no expansion in this sector. The expansion in the non-tradable sector increases base wage and attracts the labor from the tradable sector. The marginal worker entering the non-tradable sector is less efficient compared to the average existing workers, while the way the TFP is calculated treats new workers the same as the existing ones. The lower efficiency of the worker is translated to the lower imputed TFP. The existence of the mismeasurement channel makes the true TFP drop much less acutely than the measured TFP suggests.

Household

The household is one big decision maker for consumption choice. Although there are different types of workers in the household, the household only cares about the income on the aggregate level and maximizes the aggregate utility. This technique has been used in Gertler, Kiyotaki, et al. 2010. This assumption implies that there is perfect consumption insurance within the household.

The source of the income for the household is the labor income in both sectors. To make the model more tractable and intuitive, I assume the household in the economy is hand-to-mouth. So the consumption of the household is

$$C_t^H = \frac{w_t^T L_t^T + w_t^N L_t^N}{p_t}, \tag{2.9}$$

where the efficiency labor supply in the tradable sector is defined as

$L_t^T \equiv \int_0^\infty z_T g_T(z_T) G_{N|T}(\frac{w_t^T}{w_t^N} z_T | z_T) dz_T$; and the efficiency labor supply in the non tradable sector is defined as

$L_t^N \equiv \int_0^\infty z_N g_N(z_N) G_{T|N}(\frac{w_t^N}{w_t^T} z_N | z_N) dz_N$;

p_t is the price index, which is defined as

$p_t \equiv \frac{p_t^T C_t^T + p_t^N C_t^N}{C_t} = [\gamma^\xi (p_t^T)^{1-\xi} + (1-\gamma)^\xi (p_t^N)^{1-\xi}]^{\frac{1}{1-\xi}}$,

w_t^T and w_t^N are respectively the base wage of each sector.

Conceptually, it is not difficult to give the household access to the bond market.

The efficiency labor L_t^T and L_t^N are different from the numbers of workers employed, but take into the consideration of the labor productivity.

Each individual within the household is otherwise identical except for the productivity in each sector. The productivity in tradable sector is z^T, and that of the non-tradable sector is z^N, and the pair of the productivity (z^T, z^N) is drawn from some joint cumulative distribution $G(z^T, z^N)$ independently. A worker provides 1 unit of inelastic labor, so his/her efficiency labor is z^T in the tradable sector and z^N in the non-tradable sector. A worker chooses to enter the tradable sector if he/she can earn higher income there, that is, $w_t^N z^N < w_t^T z^T$; or alternatively $z^N < z_T/\omega_t$, where $\omega_t = \frac{w_t^N}{w_t^T}$. If $z_T \geq z_N \omega_t$, the household chooses to enter the non-tradable sector.

Firms

In the model, the tradable sector and the non-tradable sector are modeled very differently in terms of financial constraints. The non-tradable sector has both a collateral constraint and a working capital constraint. This modeling technique is abstracted from the fact that the non-tradable firms are on average smaller than the tradable firms, and thus they are more financially constrained. Using the US firm-level data, Chodorow-Reich 2014 shows that the employment of smaller firms is more affected by the negative credit supply shock to their banks. This is because the sticky bank-borrower relationships make it harder for smaller firms to switch from affected banks to good banks. Moreover, the small firms lack other sorts of financing rather than borrowing from banks. The paper also claims that the findings of "Small vs Big" are consistent with the existing literature, such as Duygan-Bump, Levkov, and Montoriol-Garriga 2015, explaining this by lower level of transparency within smaller firms. Beck, Demirgüç-Kunt, and Maksimovic 2005 employs unique, cross-country firm-level survey data to prove that being small in size is correlated to facing more financial obstacles. Some may suspect the correlation between size and financial constraint is only sensible within a sector. However, the result of both papers are across sectors.

Tradable Sector

There is one representative firm in the tradable sector. The firm borrows at the foreign interest rate, and hires the efficiency labor in the labor market. It is assumed that the technology and the capital stock are active in the next period.

The production function is Cobb-Douglas:

$$Y_t^T = A_{t-1}^T (K_{t-1}^T)^{\alpha_T} (L_t^T)^{1-\alpha_T}, \tag{2.10}$$

where Y_t^T is the real output of the tradable sector of the current period, and it is produced with the technology and capital stock of the previous period, A_{t-1}^T and K_{t-1}^T, as well as with the labor employment of the current period, L_t^T.

The factors market are assumed to be competitive.

The profit maximization gives two first order conditions:

$$\alpha_T A_{t-1}^T (K_{t-1}^T)^{\alpha_T - 1} (L_t^T)^{1-\alpha_T} = 1 + r_t^f \tag{2.11}$$

$$(1-\alpha_T) A_{t-1}^T (K_{t-1}^T)^{\alpha_T} (L_t^T)^{-\alpha_T} = w_t^T \tag{2.12}$$

From equation 2.11 we can see that the interest rate at which the tradable firm borrows is r_f , which is the foreign interest rate.

Equations 2.11 and 2.12 pin down the base wage of the tradable sector:

$$w_t^T = (1-\alpha_T)(\alpha_T)^{\frac{\alpha_T}{1-\alpha_T}} A_{t-1}^{\frac{1}{1-\alpha_T}} (1+r_t^f)^{-\frac{\alpha_T}{1-\alpha_T}} \tag{2.13}$$

Here, we can see that there is a one-to-one map from the true TFP of the tradable sector to the wage, so we will not consider the mismeasurement in the tradable sector.

Non-tradable Sector

The non-tradable sector has a distribution of entrepreneurs with the CDF of TFP $H(a)$, and $a \in [\underline{a}, \bar{a}]$. The entrepreneurs maximize their lifetime discounted utility. By achieving this goal, the entrepreneurs first solve a static profit maximization problem and then a dynamic optimal wealth allocation problem. In other words, in period t an entrepreneur has to decide first whether to enter the production process and then how much to spend on consumption.

It is also assumed that the technology and the capital stock are active in the next period as in the tradable sector. The static profit maximization problem can be solved using backwards induction. The entrepreneur has to choose how much to invest in the capital stock if she enters the production process. If she opts to stay out of the production, she puts the wealth less consumption in the domestic bank.

We will see in the following paragraphs that once the entrepreneur decides to enter the production process, she will invest all her wealth into the capital stock. Moreover, she faces a borrowing constraint: the debt she has to pay back in the next period has to be smaller than a fraction of the potential output less the wage bill. Furthermore, the entrepreneurs face a working capital constraint.[13] The idea of working capital constraint is that the firm must hold η units of a non-interest-bearing asset (cash) for each unit of wage payments. This constraint increases the marginal cost of labor hiring for the firm by $w_N \frac{\eta r}{1+r}$.

Let us first solve the problem of the entrepreneur decides to enter the production process in time t. She needs to solve the profit maximization problem as follows:

$$\pi_t^N = \max_{\{l_t, b_t\}} \quad p_t^N a_{t-1} k_{t-1}^{\alpha_N} l_t^{1-\alpha_N} - \tilde{w}_t^N l_t - b_t$$

$$b_t \leq \theta(p_t^N a_{t-1} k_{t-1}^{\alpha_N} l_t^{1-\alpha_N} - \tilde{w}_t^N l_t) \tag{2.14}$$

$$k_{t-1} = \hat{v}_{t-1} + \frac{b_t}{1+r_t^b}$$

where θ is a collateral constraint ratio, r_t^b is the loan rate, and $\tilde{w}_t^N = w_t^N(1 + \frac{\eta r_t^b}{1+r_t^b})$, and $\hat{v}_{t-1}$ is the wealth of the period $t-1$ that has not been consumed, which is defined as $\hat{v}_{t-1} = v_{t-1} - p_{t-1} c_{t-1}$ The capital stock used in the production is the sum of her own wealth and the borrowed money. The reason why the borrowed money is discounted by $1 + r_t^b$ is that the borrowing happens at the beginning of the period and the repayment happens at the end of the same period.

[13]This working capital constraint is a model technique widely used in the international macroeconomics field, such as Neumeyer and Perri 2005, Uribe and Yue 2006, CHANG and FERNÁNDEZ 2013 and Uribe and Schmitt-Grohé 2017. The main reason to introduce the working capital constraint is to provide a supply-side channel through which the interest rate shock matters more.

The reason to add the working-capital constraint is because the increase of foreign borrowing ϕ in the model is a supply shock: the lower borrowing cost induces the non-tradable firms to borrow more, employ more and produce more. However, more non-tradable goods push down the price, which reduces the profitability of the non-tradable sector, and hence decreases the employment. Therefore, these two forces counteract one another. The introduction of the working-capital constraint will make the increase in ϕ another positive supply shock, thus increasing the employment in the non-tradable sector. This force will drive up the base wage ratio between the non-tradable sector and the tradable sector, attracting labor flow into the non-tradable sector. The quantitative effect of the working-capital constraint is very low though.

Taking the first-order condition of the profit with respect to l_t, we get

$$l_t = [\frac{(1-\alpha_N)p_t^N a_{t-1}}{\tilde{w}_t^N}]^{1/\alpha_N} k_{t-1} \tag{2.15}$$

Using equation 2.15 to replace l_t in problem 2.14, the problem can be written as:

$$\pi_t^N = \max_{\{k_{t-1}\}} \quad x_t(a_{t-1})k_{t-1} - (1+r_t^b)(k_{t-1} - \hat{v}_{t-1})$$

$$(1+r_t^b)(k_{t-1} - \hat{v}_{t-1}) \leq \theta x_t(a_{t-1})k_{t-1}$$

where $x_t(a_{t-1})$ is the return on capital k_{-1}, and is defined as follows:

$$x_t(a_{t-1}) = \alpha_N(1-\alpha_N)^{\frac{1-\alpha_N}{\alpha_N}} [\frac{p_t^N a_{t-1}}{(\tilde{w}_t^N)^{1-\alpha_N}}]^{1/\alpha_N} \tag{2.16}$$

Since now the profit maximization problem becomes a linear problem in k_{t-1}, the result depends on the sign of the coefficient of k_{t-1}: $x_t(a_{t-1}) - (1 + r_t^b)$.

Here we use a "guess-and-verify" strategy to solve for the problem. Since here we already assume that the entrepreneur enters the production in period t, it means $k_{t-1} > 0$. Thus, we do not have to consider the equilibrium where $x_t(a_{t-1}) < (1 + r_t^b)$.

Guess that $x_t(a_{t-1}) \geq (1 + r_t^b)$. Then the borrowing constraint is binding; that is,

$$k_{t-1}(a_{t-1}) = \frac{\hat{v}_{t-1}}{1 - \frac{\theta x_t(a_{t-1})}{1+r_t^b}} \tag{2.17}$$

Profit is:

$$\pi_t^N(a_{t-1}) = x_t(a_{t-1})k_{t-1} - (1 + r_t^b)(k_{t-1} - \hat{v}_{t-1}) = \frac{(1-\theta)x_t(a_{t-1})\hat{v}_{t-1}}{1-\frac{\theta x_t(a_{t-1})}{1+r_t^b}}.$$

The return on the wealth of entrepreneurs who produce is:

$$R_t(a_{t-1}) = \frac{(1-\theta)x_t(a_{t-1})}{1-\frac{\theta x_t(a_{t-1})}{1+r_t^b}}.$$

The entrepreneurs compare the return on wealth and the deposit rate to determine whether she wants to enter the production, so there is a cutoff productivity a^* under which an entrepreneur opt to save in domestic deposit.

$$R_t(a_{t-1}^*) = \frac{(1 - \theta)x_t(a_{t-1}^*)}{1 - \frac{\theta x_t(a_{t-1}^*)}{1+r_t^b}} = 1 + r_t^d \tag{2.18}$$

where r_t^d is the domestic deposit rate.

In the bank's problem, we will see that $r_t^d > r_t^b$. Moreover $x_t(a_{t-1})$ is an increasing function on a_{t-1}. Thus, for all the producing entrepreneurs, we have $R_t(a_t) > 1 + r_t^d > 1+r_t^b$. From this inequality, we know that once in the production function, $x_t(a_{t-1}) > 1+r_t^b$. Then our initial *guess* is verified.

Moreover, the output of the non-tradable sector in period t is:

$$y_t^N = a_{t-1}k_{t-1}^{\alpha_N}l_t^{1-\alpha_N} = [\frac{(1-\alpha_N)p_t^N a_{t-1}}{\tilde{w}_t^N}]^{(1-\alpha_N)/\alpha_N} \frac{a_{t-1}\hat{v}_t}{1-\frac{\theta x_t(a_{t-1})}{1+r_t^b}}$$

The gross revenue of the non-tradable firm is

$$p_t^N y_t^N = x_t(a_{t-1})k_{t-1} + \tilde{w}_t^N l_t = \frac{\hat{v}_t}{\alpha_N}\frac{x_t(a_{t-1})}{1-\frac{\theta x_t(a_{t-1})}{1+r_t^b}} \tag{2.19}$$

After solving the static profit maximizing problem, we can solve for the dynamic problem of the entrepreneurs.

Let $I(a_t > a_t^*)$ be the indicator of producing. a_t^* is determined by equation 2.18. Since $R_t(a_{t-1})$ is an increasing function, an entrepreneur produces if she has a TFP higher than the the cutoff TFP, or she puts her wealth in the domestic bank as deposit.

Thus, the dynamic of the individual wealth is $v_{t+1} = [I(a_{t-1} > a_{t-1}^*)R_t(a_{t-1}) + (1 - I(a_{t-1} > a_{t-1}^*))(1 + r_t^d)](v_t - p_t c_t)$.

And the entrepreneur has to solve the following dynamic problem:

$\max_{c_t} \mathbb{E}\, \beta^t \ln(c_t)$

s.t. $v_{t+1} = [I(a_{t-1} > a^*_{t-1})R_t(a_{t-1}) + (1 - I(a_{t-1} > a^*_{t-1}))(1 + r_t)](v_t - p_t c_t)$

The solution for this problem is that

$$c_t = (1-\beta)\frac{v_t}{p_t}$$

$$v_{t+1} = \beta[I(a_{t-1} > a^*_{t-1})R_t(a_{t-1}) + (1 - I(a_{t-1} > a^*_{t-1}))(1 + r_t)]v_t \tag{2.20}$$

A entrepreneur's consumption is always a constant fraction of her wealth.

Bank

The bank maximizes its profit subjects to a budget constraint:

$$\max B_t - F_t - D_t$$

$$\text{s.t. } \frac{B_t}{1+r^b_t} = \frac{D_t}{1+r^d_t} + \frac{F_t}{1+r^f_t}$$

$$F_t \leq \phi B_t$$

where B_t is the face value (FV) of the loan to the non-tradable sector, F_t is the FV of the borrowing from the foreign countries, and D_t is the FV of the deposit from the non-tradable sector. ϕ, which controls how much foreign borrowing the bank can get, is the most important parameter of the model. Also, we assume here that the bank has no equity and it finances all its loans by borrowing from abroad and deposits.

In the equilibrium, we will consider the case $r_t^f < r_t^d$, so the bank would borrow from abroad to the maximum: $F_t = \phi B_t$. Moreover, because of the linear technology of the bank, it has to attain zero profits in the equilibrium, so $B_t = F_t + D_t$.

Hence, in the equilibrium, the deposit has to be a constant fraction of the total lending:

$$D_t = (1 - \phi) B_t \tag{2.21}$$

Therefore, we have a relationship among the three interest rates:

$$\frac{1}{1 + r_t^b} = \frac{1 - \phi}{1 + r_t^d} + \frac{\phi}{1 + r_t^f} \tag{2.22}$$

since $\phi \in [0, 1]$, $r_t^f \leq r_t^b \leq r_t^d$.

Market Clearing Conditions

Non-tradable Goods

The demand for the non-tradable goods has to be equal to the supply.

First, let us pin down the demand for the non-tradable goods C_t^N, which comes from two sources – the demand from non-tradable sector entrepreneurs and that from the household. The consumption aggregator is a constant elasticity substitution (CES) aggregator of tradable and non-tradable goods, that is the total consumption $C_t = [\gamma(C_t^T)^{1-\frac{1}{\xi}} + (1 - \gamma)(C_t^N)^{1-\frac{1}{\xi}}]^{\frac{\xi}{\xi-1}}$, where $\gamma \in (0,1)$, and ξ is the elasticity of substitution between tradable goods and non-tradable goods.

We can then derive the price index:

$p_t \equiv \frac{p_t^T C_t^T + p_t^N C_t^N}{C_t} = [\gamma^\xi (p_t^T)^{1-\xi} + (1-\gamma)^\xi (p_t^N)^{1-\xi}]^{\frac{1}{1-\xi}};$

and express the non-tradable consumption in terms of total consumption:

$$C_t^N = C_t(\frac{p_t^N}{p_t(1-\gamma)})^{-\xi}. \tag{2.23}$$

The derivation of the price index and the demand of non-tradable good can be found in Appendix 3.7.

Using the fact of the equilibrium condition that the demand for total consumption comes from two sources: the consumption of the entrepreneurs and consumption of the household, so $C_t = C_t^H + \int c_t dG(t)$.

Combining equations 2.9, 2.20, 2.23 and the above condition , we have

$C_t^N = (C_t^H + \int c_t dH(a_{t-1}))(\frac{p_t^N}{p_t(1-\gamma)})^{-\xi} = (\frac{w_t^T L_t^T + w_t^N L_t^N}{p_t} + \int (1-\beta)\frac{v_t}{p_t} dH(a_{t-1})(\frac{p_t^N}{p_t(1-\gamma)})^{-\xi} = (\frac{w_t^T L_t^T + w_t^N L_t^N}{p_t} + (1-\beta)\frac{V_t}{p_t})(\frac{p_t^N}{p_t(1-\gamma)})^{-\xi},$

where V_t is the aggregate wealth of entrepreneurs, defined as $V_t = \int v_d dH(a_{t-1})$

Supply of the non-tradable good is as follows:

$Y_t^N = \int_{a_{t-1}^*}^{\bar{a}} y_t dH(a_{t-1}) = \int_{a_{t-1}^*}^{\bar{a}} \frac{\tilde{w}_t l_t}{(1-\alpha_N)p_t^N} dH(a_{t-1}) = \frac{\tilde{w}_t L_t^N}{(1-\alpha_N)p_t^N}$

Since $C_t^N = Y_t^N$, we have

$$\frac{\tilde{w}_t^N L_t^N}{(1-\alpha_N)p_t^N} = (\frac{w_t^T L_t^T + w_t^N L_t^N}{p_t} + (1-\beta)\frac{W_t}{p_t})(\frac{p_t^N}{p_t(1-\gamma)})^{-\xi} \tag{2.24}$$

Loan and Deposit Market Clearing

By integration of the debt of producing entrepreneurs, we can get the aggregate loan. And by integration of the deposit of non-producing entrepreneurs, we get the aggregate deposit. Then we can link them using equation 2.21 and get the following equation:

$$(1+r_t^d)H(a_{t-1}^*) = \frac{\theta(1-\phi)}{1-\theta}\int_{a_{t-1}^*}^{\bar{a}} R_t(a_{t-1})dH(a_{t-1}) \tag{2.25}$$

By simple manipulation, we can get the expression of the integration:

$$\int_{a_{t-1}^*}^{\bar{a}} R_t(a_{t-1})dH(a_{t-1}) = \frac{(1+r_t^d)(1-\theta)H(a_{t-1}^*)}{\theta(1-\phi)} \tag{2.26}$$

The details of the derivation can be found in Appendix 3.7.

Non-tradable Sector Labor Market Clearing

By equating labor supply and labor demand in the non-tradable sector, with the law of motion of aggregate wealth of entrepreneurs in the Non-tradable sector, we can get the labor market clearing condition in the following equation:

$$\int_0^\infty z_N g_N(z_N) G_{T|N}(\frac{w_t^N}{w_t^T} z_N|z_N) dz_N = \frac{1-\alpha_N}{(1-\theta\phi)\alpha_N \tilde{w}_t^N} V_t \tag{2.27}$$

The details of the derivation of the law of motion of the aggregate wealth of entrepreneurs and the labor market clearing condition of the non-tradable sector can be found in Appendix 3.7. All the equilibrium conditions can be found in Appendix 3.7.

The Mismeasurement of TFP

Suppose the non-tradable sector has a Cobb-Douglas production function:

$$Y_t^N = A_{t-1}^N (K_{t-1}^N)^{\alpha_N} (L_t^N)^{1-\alpha_N},$$

L^N here is the efficiency labor in the non-tradable sector, and it can be expressed as $L^N = q^N \bar{z}^N$, where q^N is the share of labor that works in the non-tradable sector.

The mathematical definition is $q^N = \int_0^\infty g_N(z^N) G_{T|N}(\frac{w^N}{w^T} z^N|z^N) dz^N$,

and $L^N = \int_0^\infty z^N g_N(z^N) G_{T|N}(\frac{w^N}{w^T} z^N|z^N) dz^N$.

It follows that $\bar{z}^N = \frac{L^N}{q^N}$

.

We measure TFP in macroeconomics as the Solow residual, so the true TFP growth rate is

$$\hat{A}^N(true) = \hat{Y}^N - \alpha_N \hat{K}^N - (1-\alpha_N)(\hat{q}^N + \hat{\bar{z}}^N) \tag{2.28}$$

However, for a macro-econometrician, the labor efficiency change is unobservable; therefore, when calculating the Solow residual, what is actually estimated is following:

$$\hat{A}^N(est) = \hat{Y}^N - \alpha_N \hat{K}^N - (1-\alpha_N)\hat{q}^N = \hat{A}^N(true) + (1-\alpha_N)\hat{\bar{z}}^N \tag{2.29}$$

We can define the elasticity of average sectoral labor efficiency with respect to the size of the sector:

$$\zeta = \frac{d\bar{z}^x}{dq^N}\frac{q^N}{\bar{z}^N} \tag{2.30}$$

Now, the estimated TFP in equation 2.31 can be transformed to:

$$\hat{A}^N(est) = \hat{A}^N(true) + (1-\alpha_N)\zeta\hat{q}^N \tag{2.31}$$

As long as this elasticity ζ is not zero, there will be mis-measurement.

It is easy to see that $\xi > -1$. In the definition of $\bar{z}^N$, if the increase of q^N does not change L^N, ζ would be -1, but the amount of efficiency labor L^N also increases when there are more people enter the sector. Therefore ζ should be bigger than -1.

The interesting point is to determine the sign of the elasticity. If $\xi < 0$, then when the sector expands, the average sectoral labor efficiency decreases, which leads to an underestimation of sectoral TFP.

According to Young 2014, we can have the following theorem:

Theorem: If the following two conditions are satisfied:

1.the distributions of z_T and z_N are independent: $G(z_T, z_N) = G_T(z_T)G_N(z_N)$**;**

2.$\frac{g_x(z_x)z_x}{G_x(z_x)}$ **(where** $x = T, N$**) are decreasing functions,**

then $\zeta \leq 0$**.**

The first condition is basically saying that if a person is born to be a good chef, he/she may or may not be an efficient engineer, or a good micro theory professor may struggle in the field of macro economics. The second condition is more like a technical requirement, and all widely used distributions satisfy this property. The proof of the theorem can be found in Appendix 3.7.

Let's see how it works out in an analytical example.

Besides the assumption that z^T and z^N are independent, let us assume furthermore that cdfs G_T and G_N are exponentially distributed over $[0, \infty]$; that is, $G_T(z^T) = 1 - e^{-\lambda_T z^T}$, and $G_N(z^N) = 1 - e^{-\lambda_N z^N}$. Accordingly, pdfs are $g_T(z^T) = \lambda_T e^{-\lambda_T z^T}$ and $g_N(z^N) = \lambda_N e^{-\lambda_N z^N}$.

With the assumption on the distribution of the labor quality in the two sectors, we can compute the closed form efficiency labor in both sectors as follows:

$$L^T = \frac{1}{\lambda_T} - \frac{\lambda_T}{(\lambda_T + \lambda_N/\omega)^2} \tag{2.32}$$

$$L^N = \frac{1}{\lambda_N} - \frac{\lambda_N}{(\lambda_N + \lambda_T \omega)^2} \tag{2.33}$$

Moreover, we can compute the quantity of labor as follows:

$$q^T = \frac{\lambda_N}{\lambda_N + \lambda_T \omega} \tag{2.34}$$

$$q^N = \frac{\lambda_T \omega}{\lambda_N + \lambda_T \omega} \tag{2.35}$$

The sum of the quantity of labor in two sectors equal to the total quantity of labor which is normalized to 1, that is, $q_T + q_N = 1$.

Then the average quality of labor in each sector can be computed as follows:

$$\bar{z}^T \equiv \frac{L^T}{q^T} = \frac{1}{\lambda_T} + \frac{\omega}{\lambda_N + \lambda_T \omega} \tag{2.36}$$

$$\bar{z}^N \equiv \frac{L^N}{q^N} = \frac{1}{\lambda_N} + \frac{1}{\lambda_N + \lambda_T \omega} \tag{2.37}$$

Then it is easy to see that when the wage ratio ω increases, the labor moves out from the tradable sector into the non-tradable sector, and the average labor quality of the tradable sector increases while that of the non-tradable sector decreases.

2.6 Numerical Result

In this section, I present a calibrated version of the model and show that the prediction of this calibrated model matches the data. It also shows that the mismeasreument channel contributes much more than the misallocation channel to the TFP drop in the model.

Calibration and Impulse Response Functions

Following Reis 2013, one period of the model is set to be four years to justify the absence of nominal rigidities and the assumption of the i.i.d firm-level productivity shock. The risk-free rate r_f is set to be 0.08 and $\beta = 0.84$ is picked in order to make sure that the average steady-state capital return is around 0.16.

According to Table 2.3, setting $\alpha_N = 0.3$ and $\alpha_T = 0.3$ is a good approximation and close to the convention of the calibration of the Cobb-Douglas production function.

The productivity level of the tradable sector A_T is set to be the average productivity of the non-tradable sector: $A_T = \exp(0) = 1$.

The coefficient θ measures the percentage of the finance that comes from the bank. The BIS data shows that the credit from the bank to a non-financial corporation should be around 0.3. Since it is even more difficult for the non-tradable firms to borrow from the banks, I set $\theta = 0.2$.

The elasticity of substitution $\xi = 2$ is a very conventional number. The coefficient that governs the share of the non-tradable consumption $\gamma = 0.5$, which is also a conventional number.

The distribution of the productivity of the non-tradable firms is log-normal, which matches the full sample TFP distribution of the construction sector of Spain.

The working capital constraint parameter η is set to be 0.5. According to Uribe and Schmitt-Grohé 2017, this parameters means that the firm needs to hold half of the wage bill in advance, which means two years of wage bill in this model. However, to modify the parameter to a smaller number does not affect the prediction of the model.

The distribution of labor quality in the tradable sector and non-tradable sector matches the distribution of the non-observable individual characteristics from the analysis of the SES of Eurostat for Spain.

The overview of the calibration is listed in Table 2.7.

Table 2.7: Calibration

Parameters	β	r_f	α_N	α_T	A^T	η	θ	ξ	γ
	0.84	0.08	0.3	0.3	1	0.5	0.2	2	0.5
Distribution of a			Lower Bound (a_1)			Upper Bound (a_2)		μ	σ
Log-normal			exp(-8)			exp(4)		0	0.45
Distribution of z^N			Lower Bound (z_1^N)			Upper Bound (z_2^N)		μ	σ
Log-normal			exp(-8)			exp(3)		-3	1.98
Distribution of z^T			Lower Bound (z_1^T)			Upper Bound (z_1^T)		μ	σ
Log-normal			exp(-7)			exp(5)		-2.2	1.2

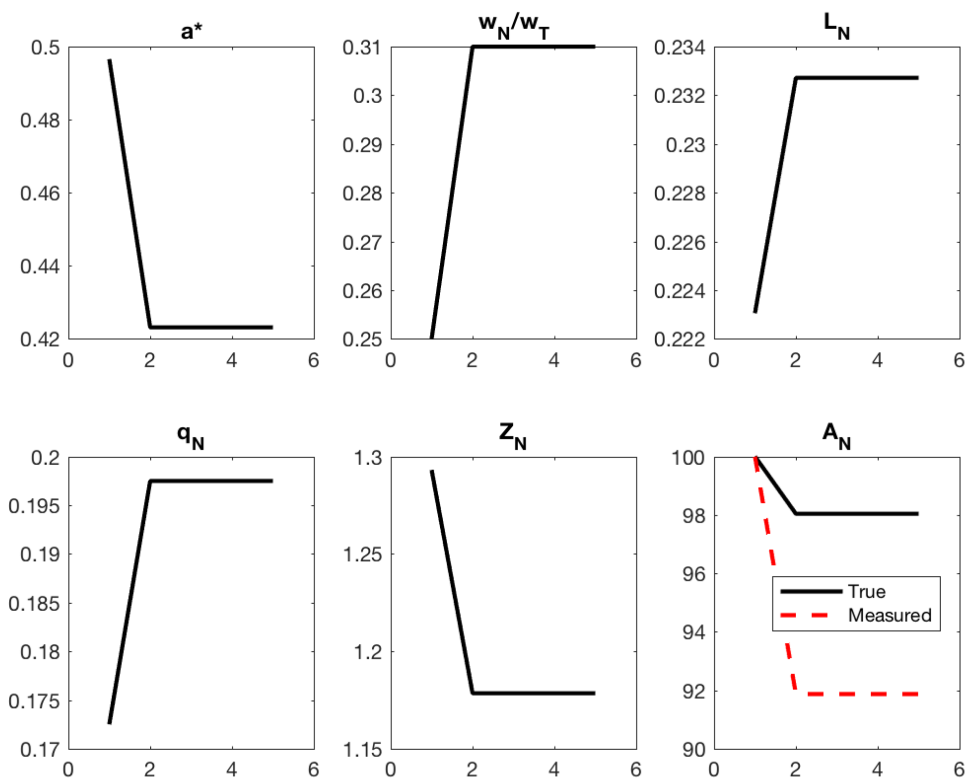
Figure 2.11 shows the impulse responses of the key variables in the model to explain the TFP drop in the non-tradable sector, and thus the entire economy. The shock here is that

ϕ rises from 0 to 0.6 in the first period. The model jumps from one steady state to the new steady state very quickly and stays there. According to equation 2.18, the lowered deposit rate will induce a lower cutoff productivity a^*, at which an entrepreneur enters the market and produces. The lowered cutoff a^* triggers the average productivity to drop, but only to a limited amount. That is the black solid line in the "A_N" graph of Figure 2.11.

The shock also changes the borrowing cost of the firms in the non-tradable sector to a much lower level, which can be seen from equation 2.22. This leads to an expansion of the non-tradable sector. Therefore, the wage ratio between the non-tradable sector and tradable sector $\omega = \frac{w_N}{w_T}$ increases. The relative increase of wage in the non-tradable sector attracts people to move into this sector, which explains the increase of the number of people in graph "q_N", and also the total efficiency labor increase in graph "L_N." However, the average quality of the non-tradable sector, as in graph "Z_N," decreases due to the Theorem in subsection 2.5. The lowered average quality explains the measured TFP drop, as shown by the red dashed line in graph "A_N".

Therefore, the key graph in Figure 2.11 is graph "A_N." The most important message from this graph is that the measured TFP drop is much worse than the one without any mismeasurement of the labor quality. Alternatively speaking, this means that if we can measure the labor quality correctly and take it into the consideration in TFP estimation, then corrected TFP drop will be much more mild compared to the TFP data we see now. This prediction of the TFP drop is in line with the TFP decomposition that I perform in Figure 2.10, showing that the mismeasurement channel dominates the misallocation channel in explaining the TFP drop of the non-tradable sector.

Figure 2.11: Impulse Responses/Trasitional Paths



The calibration of the model is listed in Table 2.7.

2.7 Conclusion

This paper has documented differentiated TFP growth paths between expanding sectors and non-expanding sectors for southern European countries between 1996 and 2007. Careful analysis of aggregate data and micro-level data shows that capital misallocation cannot explain this phenomenon, but labor quality mismeasurement can. If labor quality is treated properly, the true TFP drop of the expanding sector would be much smaller. Therefore, the true TFP drop of the total economy would be smaller as well. One policy implication we draw from this paper is that we should review the policy targeting the misallocation problem. Also this paper calls for a revision of TFP calculation that incorporates more labor quality than the state-of-the-art research such as KLEMS does.

Chapter 3

State Reform and China's Productivity Deceleration: Firm-level Evidence[1]

3.1 Introduction

The end of the 20th century and beginning of the 21st century brought extraordinarily high growth in China. This has been attributed to rapid capital accumulation, improvements in technology adoption, and remarkable changes in the organization of production between state and private agents. The drivers of the recent Chinese deceleration, however, are still unclear. Using a combination of firm- and sector-level evidence, we study the drivers of this deceleration. We argue that past growth gains from state-ownership reform have lost steam recently, contributing to a perceived deceleration and even decline in measured TFP growth. Furthermore, we find that deceleration in measured TFP within firms is not necessarily driven by worsening technologies, but from past investments resulting in over-capacity problems.

This paper has three main contributions. First, we document TFP dynamics in Chinese

[1]This chapter is co-authored with Jorge Alvarez and Grace Li. Part of the chapter was written when Tuo Chen was doing summer internship in the IMF.

manufacturing at both the sectoral and firm level using several techniques from the literature. These include Cobb-Douglas specifications with and without constant return to scale, as well as instrumental variable techniques proposed by Olley-Pakes (1996), Levinsohn-Petrin (2003) and De-Locker (2011). We compute firm-level TFP measures using data from the Chinese Industrial surveys, and compare trends and dynamics to aggregate TFP computed from sector-level data from China's Industrial Statistical Yearbook. All procedures, using both firm and sector level data, reflect the same patterns for TFP growth. They show impressive growth in the early 2000s which decelerated after 2007 and turned flat or slightly negative after 2011.

Second, we decompose past TFP gains and deceleration between firms and state-ownership status using a novel statistical decomposition technique. The exercise decomposes TFP changes into a between SOE/Non-SOE component (driven by past privatization), and within SOE/Non-SOE. Furthermore, within SOE/Non SOE components are further decomposed into between-firm reallocation and within-firm TFP change components. This statistical decompositions allows for an assessment of the quantitative importance of past privatization efforts as well as the role of reallocation of capital labor and capital between firms in both state-controlled and private production.

Third, we consider the role of capital underutilization in explaining the recent deceleration. We do this by linking subsectors covered by the Chinese Industrial Survey to sub-sector level production and capacity data from Chinese statistical year book. The data shows an moderate improvement of capital utilization metrics in most sectors up to 2007, with a sharp decline in the years where TFP is decelerated. An assessment of the quantitative importance of the capital utilization channel indicates that this can explained a significant share of the Chinese deceleration.

The rest of the paper proceeds as follows. Section 3.2 describes the data and procedures used in computing TFP at the firm and sector level. Section 3.3 documents the aggregate trends of these measures. Section 3.4 documents gaps in TFP between SOE and non-SOEs and their evolution over time. Section 3.5 conducts a statistical decomposition of aggregate TFP changes between and within firms. Section 3.6 evaluates the role of capital utilization in explaining TFP dynamics. Section 3.7 concludes.

3.2 Empirical strategy

Data Description

We employ two main sources of data in this paper. Aggregate data is downloaded from the China Industry Statistical Yearbook, including the sales income, sales cost, number of people employed, and total assets. This is complemented with the aggregate wage bill from China's Labor Statistical Yearbook. The two-digit sectoral price data is downloaded from the China Statistical Yearbook[2].

Firm-level data is from Chinese Industrial Survey (1998 - 2013). This dataset has been widely used in the literature, including the seminal work on capital by Chang-Tai Hsieh 2009. The main difference of our dataset compared to previous ones is that the it covers a

[2]The China Statistical Yearbook data can be accessed through the website of National Bureau of Statistics of China, while the China Industry Statistical Yearbook and the China Labor Statistical Yearbook can be accessed through the website of China Knowledge Resource Integrated Database (http://www.cnki.net/).

longer time span. While the literature has focused on the period between 1998 and 2007, we expand this to include years up to 2014.

In doing this, there are several gaps in the data which we attempt to circumvent. The commonly used sample of the Chinese Industrial Survey covering 1998 - 2007, is relatively homogeneous: each year has almost identical variables and a unique identifier. In contrast, the data after 2007 presents several shortcomings. First, the 2008 year data has no firm-level identifier and 2009 misses one-third of the identifiers. This complication make it is impossible to include 2008 and 2009 data in the panel dataset. Because of this, we prepare two versions of data set. One version includes 2008 and 2009 data which we treat as cross-sectional dataset for the calculation of the yearly cross-sectional aggregate statistics. The other version excludes the data of these two years and is a panel dataset at the firm-level.

Second, some variables needed for the proper calculation of firm-level TFP are missing in the later years. In particular, the key variable of value added, which serves as output in the production function, is missing after year 2007. To address this, we calculated our own measure of total factor productivity that does not subtract intermediate inputs from total production. We validate this approach by comparing our measure to the traditional measure of TFP using the pre-2007 data. We will show in the next subsection that the shortcoming does not have great effects on measured TFP growth in the 1998-2007 period. Finally, the 2010 year data is incomplete along several dimensions, and we therefore exclude this year from our sample.

TFP measurement methodology

In this section, we describe the different methodologies used to measure TFP at both the aggregate and the firm level.

We start with the estimation method using aggregate data. This assumes a Cobb-Douglas production function and constant returns to scale. We use value added as a measure of output; therefore, the production function has two inputs: capital and labor. The weight parameter is determined by the labor share, which is calculated as the total wage bill over the value added. TFP in this approach is simply calculated as a Solow residual. The whole procedure can be summarized by the following set of equations:

$$
\begin{aligned}
&\mathrm{VA}_t = \text{Sales Income}_t - \text{Sales Cost}_t \\
&\text{Real VA}_t = \frac{\mathrm{VA}_t}{P_t} \\
&\alpha_t^L = \frac{w_t L_t}{\mathrm{VA}_t} \\
&\alpha_t^K = 1 - \alpha_t^L \\
&K_t = \frac{\text{Total Asset}_t}{P_t^K} \\
&A_t = \frac{\text{Real VA}_t}{L_t^{\alpha_t^L} K_t^{\alpha_t^K}}
\end{aligned}
\tag{3.1}
$$

where VA_t stands for the valued added, and Real VA_t is VA_t deflated by the producer price index P_t, capital measure K_t is equivalent to assets deflated by the price index of investment in fixed assets P_t^K, $w_t L_t$ is the total wage bill, α_t^L and α_t^K are respectively the labor share and capital share. Variables "Sales Income", "Sales Cost", P, P^K, L_t, $w_t L_t$ and "Total Asset" are all directly observed.

The analogous Cobb-Douglas constant returns to scale approach is also applied to the firm-level data as well, with some modifications. The value added, assets, labor and wage bill are now all calculated at the firm level. Ideally, the producer price index and investment price index would be observed at firm-level as well, but firm-level prices are not available in our data set. We instead use use the two-digit sectoral producer price index and the same industrial level investment price index as in the aggregate approach. The labor share and capital share here are measured at the two-digit sectoral level. The estimation is summarized by the following equations:

$$\text{Real } va_{ist} = \frac{va_{ist}}{P_{st}}$$

$$\alpha^L_{st} = \frac{\sum\limits_{i \in s} w_{ist} L_{ist}}{\sum\limits_{i \in s} \text{va}_{ist}}$$

$$\alpha^K_{st} = 1 - \alpha^L_{st} \tag{3.2}$$

$$K_{ist} = \frac{\text{Fixed Asset}_{ist}}{P^K_t}$$

$$A_{ist} = \frac{\text{Real } va_{ist}}{L_{ist}^{\alpha^L_{st}} K_{ist}^{\alpha^K_{st}}}$$

where va_{ist} stands for the valued added of firm i in the two-digit sector at time t, and Real va_{ist} is va_{ist} deflated by the two -digit sectoral producer price index P_{st}, capital measure K_{ist} reflects reported fixed assets deflated by the price index of investment in fixed assets P^K_t[3], $\sum\limits_{i \in s} w_{ist} L_{ist}$ is the total wage bill of the firms within two-digit sector s, α^L_{st} and α^K_{st} are respectively the labor share and capital share in sector s. Variables va_{is}, P_s, P^K, L_{is}, $w_{is}L_{is}$ and Total Asset$_{is}$ are all directly observed.

In addition, we compute firm-level TFP using three methodologies that exploit the panel dimension of the dataset: Olley and Pakes 1996, Levinsohn and Petrin 2003 and De Loecker 2011. Both Olley and Pakes 1996 and Levinsohn and Petrin 2003 try to reduce the bias induced by the correlation between firm-level productivity and input choices. The bias

[3] When using total assets instead, results do not change significantly.

comes from the possibility that a specific firm may have private information about its own productivity and make input decisions accordingly. This correlation between inputs and productivity makes the OLS estimates biased.

The key assumption made in Olley and Pakes 1996 is that the firm-level productivity is a function of investment and this function is invertible. The paper also assumes a Cobb-Douglas production function, but it no longer assumes constant returns to scale. More specifically, the approach is designed to estimate the coefficients of the following equation

$$y_{ist} = \beta^l l_{ist} + \beta^k k_{ist} + \Sigma_s \delta_s Ind_s + \Sigma_t \delta_t year_t + \beta^{\text{SOE}} SOE_{ist} + \beta^{exp} exp_{ist}$$
$$+\omega_{ist}(age_{ist}, k_{ist}, inv_{ist}) + \varepsilon_{ist} \tag{3.3}$$

where lower-case letters are the log values of the variables: $y_{ist} = \ln(\text{Real } VA_{ist})$, $l_{ist} = \ln L_{ist}$, $k_{ist} = \ln K_{ist}$, and ω_{ist} is the residual TFP that is not captured by the observables. age captures firm's the length of existence. inv is the log value of firm's investment. Ind_{ist} is the variable for two-digit sector. $year_{ist}$ captures the time fixed effect. SOE_{ist} is a dummy indicate whether a firm is a state-owned enterprise. And exp_{ist} is a dummy indicate whether a firm exports or not.

The goal is to estimate β_l and β_k and back out the production function. Then the TFP can be measured as the firm-level Solow residual. Since estimating equation 3.3 using OLS produces biased estimated coefficients due to dependence of ω on k [4], a two-step

[4]There are ways to deal with the bias of β_l if ω is a function of l too. In the estimation we employ the

instrumental approach is needed. In the first step, we run the following regression:

$$y_{ist} = \beta^l l_{ist} + \Sigma_s \delta_s Ind_s + \Sigma_t \delta_t year_t + \beta^{\text{SOE}} SOE_{ist} + \beta^{exp} exp_{ist} \phi(age_{ist}, k_{ist}, inv_{ist}) + \varepsilon_{ist}, \tag{3.4}$$

where $\phi(age_{ist}, k_{ist}, inv_{ist}) = \beta^k k_{ist} + \omega(age_{ist}, k_{ist}, inv_{ist})$. The functional form of $\phi(age_{ist}, k_{ist}, inv_{ist})$ is approximated by a higher-order polynomial of the input variables. Moreover, we assume that ω_{ist} follows a Markov-chain process: $\omega_{ist+1} = g(\omega_{ist}) + \mu_{ist+1}$, and μ_{ist} is iid. The second-step regression can be therefore expressed

$$\widehat{\phi}_{ist+1} = \beta^k k_{ist+1} + g(\omega(age_{ist}, k_{ist}, inv_{ist})) + \eta_{ist} \tag{3.5}$$

where the function $g(\omega(., ., .))$ can also be approximated by a high-order polynomial.

The methodology in Levinsohn and Petrin 2003 is very similar to Olley and Pakes 1996. But instead of using investment as the proxy for the unobserved productivity, intermediate inputs are used. That is

$$y_{ist} = \beta^l l_{ist} + \beta^k k_{ist} + \Sigma_s \delta_s Ind_s + \Sigma_t \delta year_t + \beta^{\text{SOE}} SOE_{ist} + \beta_{exp} exp^{ist} \tag{3.6}$$

$$+\omega_{ist}(age_{ist}, k_{ist}, m_{ist}) + \varepsilon_{ist}$$

---

methodology in Ackerberg, Caves, and Frazer 2015 to correct for the estimate of β_l. But for the purpose of illustration, we do not talk about it here.

where m_{iit} is the measure of total operation inputs deflated by the intermediate input price index.

For both Olley and Pakes 1996 and Levinsohn and Petrin 2003 approaches, estimated firm-level productivity is given by

$$a_{ist} = y_{ist} - \widehat{\beta}^k k - \widehat{\beta}^l l \tag{3.7}$$

The final approach is that of De Loecker 2011. This addresses the implicit assumption made by Olley and Pakes 1996 and Levinsohn and Petrin 2003 that the difference between the firm-level price and two-digit sectoral level price is not correlated with the input choice. This assumption could be broken, for example, when a monopolistic firm could charges higher prices than the average sectoral price and enlarges its size (in terms of value added) as a result. In this scenario, $P_{ist} - P_{st}$ could be positively correlated with capital and labor. The methodology in De Loecker 2011 take the potential bias caused by the price difference seriously and incorporate a CES demand system into the estimation. The regression specification is as follows:

$$\begin{aligned} y_{ist} = {} & \beta^{l*} l_{ist} + \beta^{k*} k_{ist} + \beta^s y_{st} + \Sigma_s \delta_s Ind_s + \Sigma_t \delta year_t + \beta^{\text{SOE}} SOE_{ist} \\ & + \beta^{exp} exp_{ist} + \omega_{ist}(age_{ist}, k_{ist}, m_{ist}) + \varepsilon_{ist} \end{aligned} \tag{3.8}$$

where y_{st} is the log value of the real term of two-digit sectoral value added, defined as $y_{st} \equiv \ln(\Sigma_{i \in s} va_{ist}) - \ln(P_{st})$, and β_s is interpreted as the inverse of the elasticity of substitution of sector s. TFP is therefore estimated as:

$$a_{ist} = (y_{ist} - \widehat{\beta}^{k*} k - \widehat{\beta}^{l*} l - \widehat{\beta}^{s} y_{st}) \frac{1}{1 + \widehat{\beta}^{s}} \tag{3.9}$$

3.3 TFP growth deceleration

This section shows the results from the TFP estimation procedures described above. First, we show that all TFP measures from different methodologies are highly correlated and the main conclusions are robust to different estimation procedures. Second, we show the trends of TFP over the period, which show a TFP deceleration in the most recent years.

Table 3.1 and table 3.2 shows how closely the four measures of firm-level TFP growth correlated with each other. "DL" stands for the methodology of TFP measure using De Loecker 2011 described in equation 3.8 , "LP" for Levinsohn and Petrin 2003 in equation 3.6, "OP" for Olley and Pakes 1996 in equation 3.3 and "CD" for the Cobb-Douglas methodology in equation 3.2. The reason for having two tables with high similarity is that the variable value added is only observable between years 1999 and 2007. After year 2007, we have to construct our own measure of value added. This approach is reflected in the "Pseudo VA" measure used in table 3.2, which is calculated as the difference between the firm-level "sales income" and "sales cost". Because of the gaps in value added availability, we present correlations of TFP estimates using value added from 1998 to 2007 in 3.1 and TFP estimates using "Pseudo VA" from 1998 to 2013 in table 3.2. In both samples and both types of estimation approach, we find high correlation across all measures.

Table 3.1: DlnTFP Correlation measured by VA

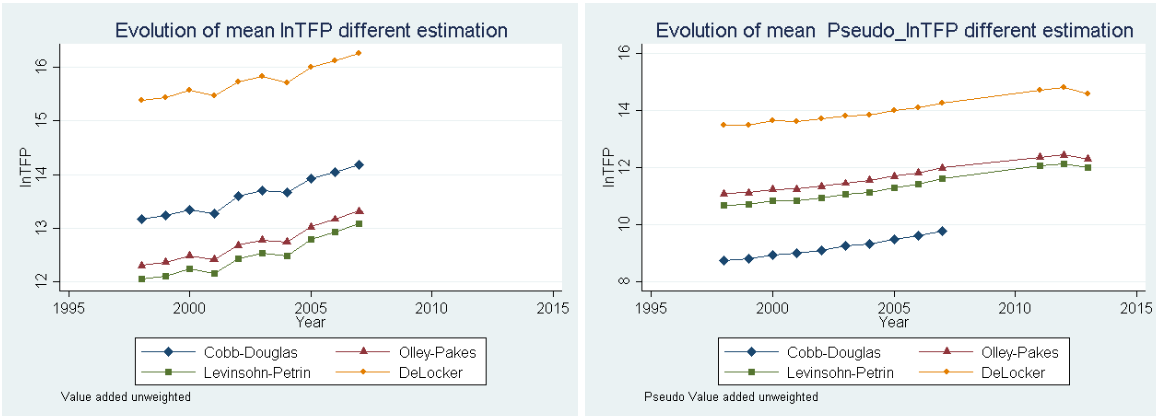
Variables	DL	LP	OP	CD
DL	1.000			
LP	0.998	1.000		
OP	0.995	0.997	1.000	
CD	0.942	0.945	0.966	1.000

Table 3.2: DlnTFP Correlation measured by Pseudo VA

Variables	DL	LP	OP	CD
DL	1.000			
LP	0.997	1.000		
OP	0.991	0.997	1.000	
CD	0.969	0.977	0.982	1.000

Figure 3.1 shows the unweighted average TFP growth path measured by different methodologies. The left panel uses the officially calculated value added while the right panel uses the "Pseudo value added" calculated as the difference between "sales income" and "sales cost". The level difference by different measures of TFP is caused by the normalization, therefore does not reveal any information. The informative pattern in this figure is the trend. We observe that the growth path of TFP is very similar across different measures in both sub-figures. This observation is consistent with the high correlation in table 3.1 and table 3.2. The right panel tells us that starting around year 2011, the TFP growth rate starts to decline, and it even becomes negative from year 2012 to year 2012.

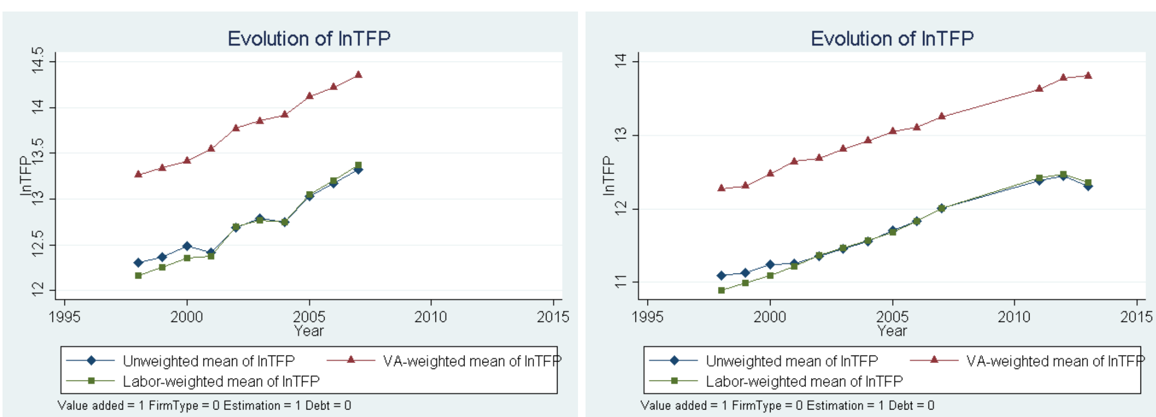
Figure 3.2 plots the mean lnTFP paths by different weights using the firm-level TFP measured by methodology in De Loecker 2011. Similarly, the left panel uses officially calculated value added and the right panel uses the "pseudo value added". The slowing



(a) Directly Observed VA (b) Pseudo VA = Sales Income - Sales Cost

Figure 3.1: Unweighted Mean of lnTFP by different measures

down of TFP growth starting from year 2011 can be observed in any type of weighted mean lnTFP on the right panel, be it the unweighted, value added weighted or labor weighted mean lnTFP. Another interesting point of figure 3.2 is that the labor weighted mean is about the same as the unweighted mean, while the value-added weighted mean is much higher in both sub-figures. The reason for that is that the firms with higher TFP tend to have a higher value added. However there is no clear correlation between the labor employment and TFP.



(a) Directly Observed VA (b) Pseudo VA = Sales Income - Sales Cost

Figure 3.2: Mean of lnTFP by different weights

Figure 3.3 compares the firm-level TFP measure to the aggregate TFP measure, and shows that both measures have the same trend. The red curve plots the unweighted mean of value-added lnTFP measure, and the blue curve unweighted mean of pseudo-value-added lnTFP measure using the methodology in Olley and Pakes 1996 with the firm-level data. And we find that the two have the same trend between the period from year 1998 to 2007. The green curve plots the aggregate lnTFP measure using equation 3.1. It can be seen that after 2011, we observe the same reversal of TFP growth path that we observe in the firm-level data. Moreover, the aggregate TFP series has a longer historical data, indicating that after 2013, the TFP continues to drop.

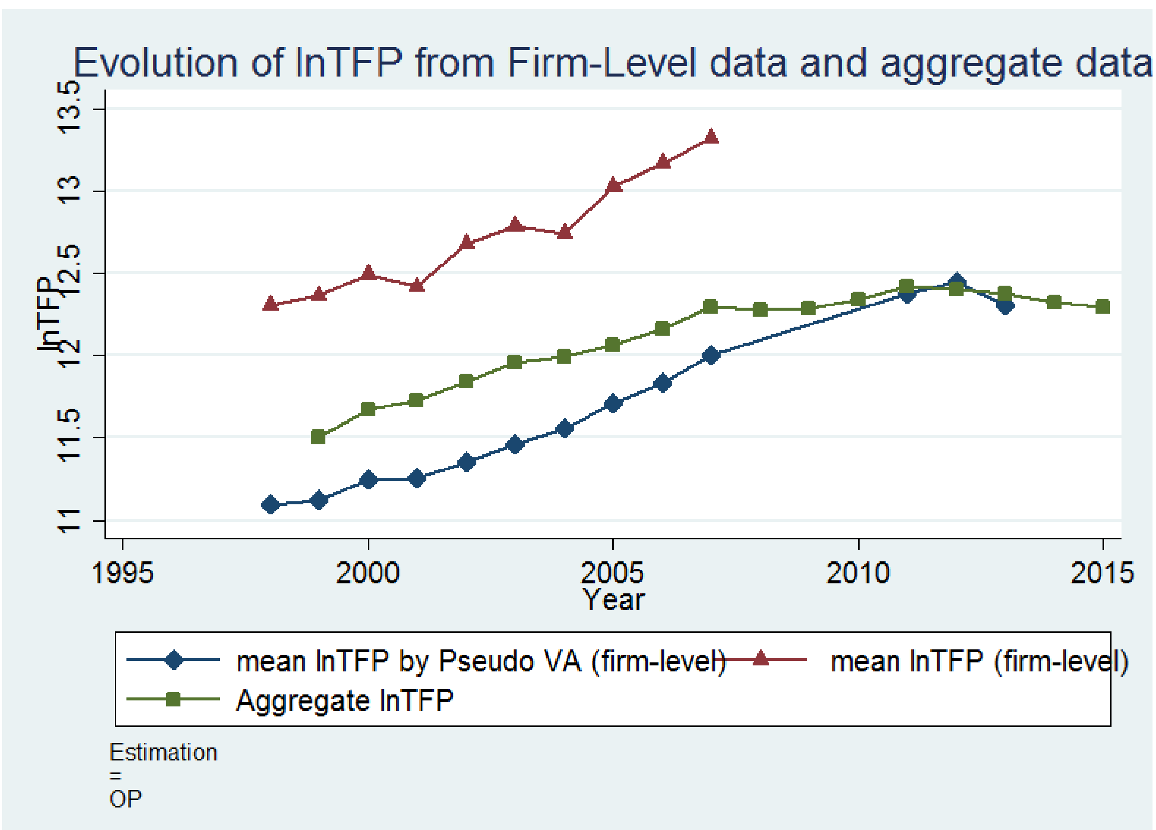


Figure 3.3: Firm-level Estimation and Aggregate Estimation

3.4 The Role of SOEs in TFP

In this section, we demonstrate that the state-owned enterprises (SOEs) are different from the non-state-owned-enterprises (Non-SOEs) in many aspects and how the timing the growth and slowdown in privatization coincides with the timing of TFP growth and growth and slowdown of manufacturing TFP. Moreover, we show evidence that the TFP deceleration cannot be due to any sectoral difference since the growth pattern of TFP of almost all sectors are the similar to that of the whole manufacturing sector.

Productivity of SOEs vs Non-SOEs

The empirical framework in this subsection is as follows:

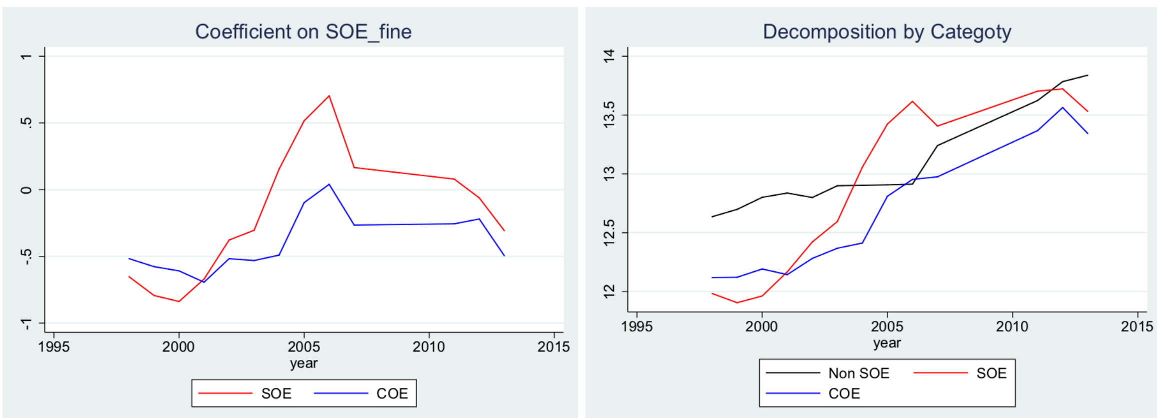
$$lnTFP_{it} = \beta_{0t} + \Sigma_g^{N_g} \beta_{gt} D_{it}^g + \varepsilon_{it} \tag{3.10}$$

where i is the firm identifier, t is the year subscript, g is the characteristic group subscript. N_g stands for the number of groups. D_{it}^g is a dummy variable, defined as $D_{it}^g = 0$ if $i \notin g$ and $D_{it}^g = 1$ if $i \in g$.

When we divide firms into three categories: SOEs, collectvity-owned enterprises (COEs)[5] and non-SOEs, and run the regression in equation 3.10 year by year, we can plot the graph in 3.4. Here we set the baseline group to be the group of non-SOE firms. That is why in the left panel, there are only two series of coefficients standing for the SOEs

[5]COEs can be considered as one type of SOEs, which are owned by local governments. We will show later that COE are less important in terms of size compared to the other two types.

and COEs while on the right panel there are three lines including the one for the baseline group. Why we cannot have clear interpretation of the coefficnets time series, the predicted average of lnTFP in has different patten. From 1998 to 2004, SOEs are relatively less productive compared to the Non-SOEs. Then SOEs catches up with the Non-SOEs in terms of productivity and even surpass the Non-SOEs after 2005. However, Starting from year 2011, we see a decelaraton of TFP growth in SOEs but not in non-SOE firms.



(a) Coefficients

(b) Predicted average lnTFP

Figure 3.4: Decomposition by SOE category

Figure 3.5 plots the dispersion of the marginal revenue product of capital (MRPK). The calculation of MRPK follows Chang-Tai Hsieh 2009. And the dispersion is measured as the standard deviation of the log value of MRPK. The definition is shown in equation 3.11.

$$MRPK_{it} \propto \frac{va_{it}}{K_{it}} \tag{3.11}$$

$$\text{Dispersion}_t = std(\ln MRPK_{it})$$

Now we divide firms by sectors and run the same year-by-year regression in equation

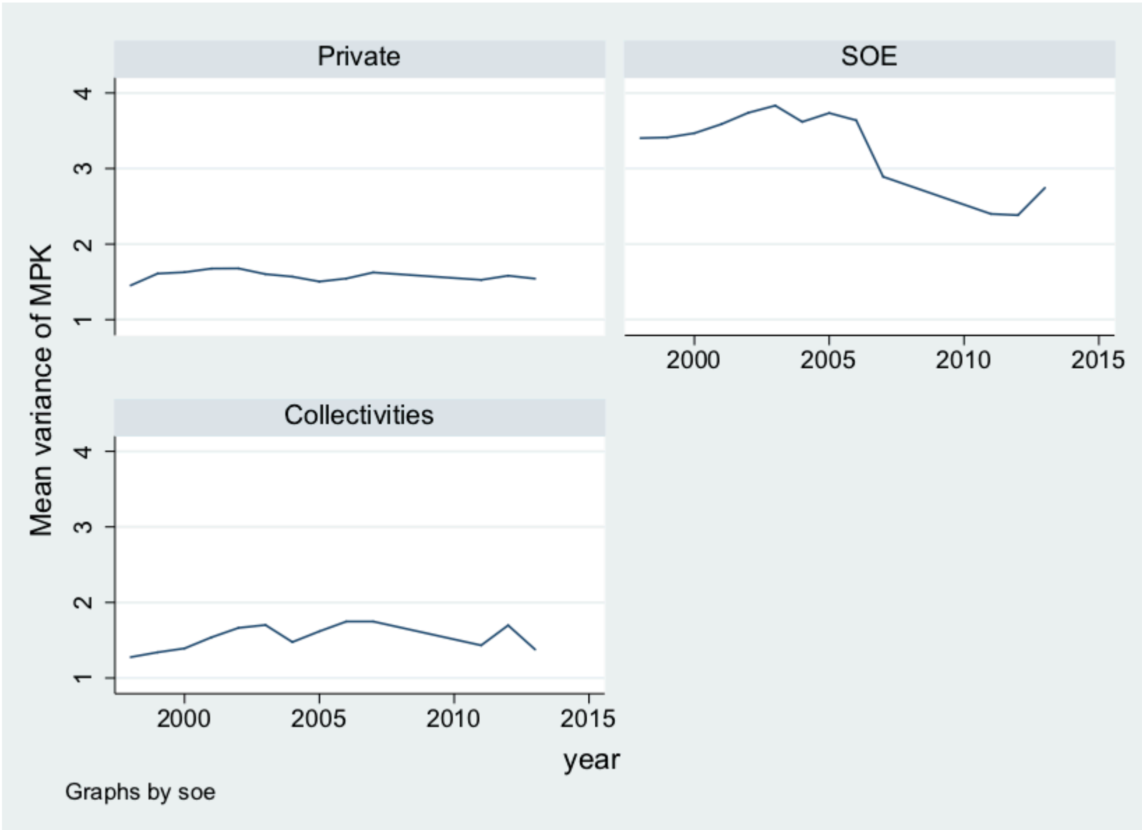


Figure 3.5: Dispersion of MRPK

3.10. We can get the predicted average lnTFP by sectors as shown in Figure 3.6. Here the sectors are grouped by their main characteristics for the purpose of clear presentation. Although it seems a bit messy in early years, the average lnTFP of all sectors displays the dip that is similar to that of the average lnTFP of the total industry as a whole. This means that the deceleration of TFP growth exists in every sectors, which contrasts to the observation that it does not in every SOE category.

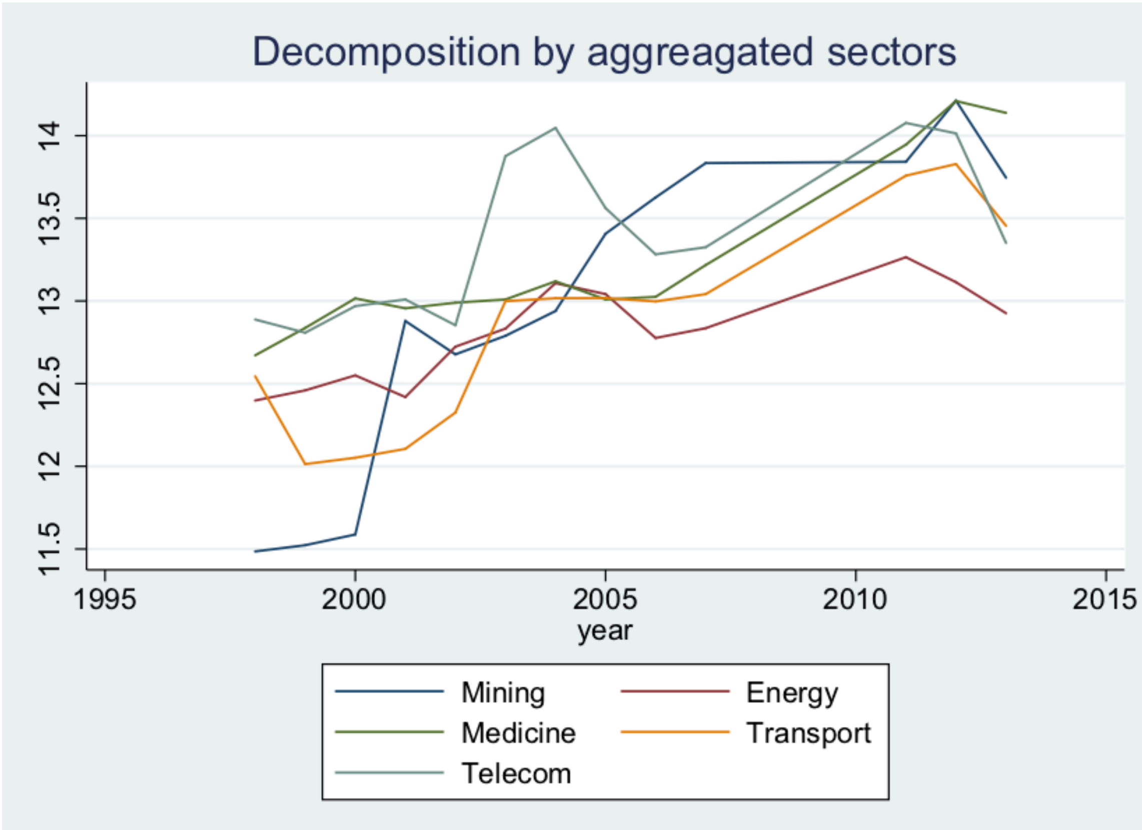


Figure 3.6: Decomposition by Sectors

Privatization Slowing Down

In this subsection, we show more difference between the SOEs and non-SOEs. More specifically speaking, we are going to show that the privatization process has slowed down and even reversed. And a possible reason for that is that the borrowing cost for non-SOEs have gone up too much.

Figure 3.7 presents a mirroring pattern by construction. The blue curve presents the share of real capital of non-SOEs and the red curve that of SOEs. From year 1998 to 2011, the share of real capital of non-SOEs is always increasing except for year 2004. This is mainly because of the privatization process in China. However, this privatization process

Table 3.3: Summary Statistics Capital by Ownership

	Ownership			
year	**POE** %	**SOE** %	**COE** %	**FOE** %
1998	12.1	57.7	9.4	20.7
1999	13.8	55.2	8.8	22.2
2000	22.9	48.0	7.8	21.2
2001	38.6	33.7	5.8	21.9
2002	43.3	29.5	4.8	22.4
2003	44.6	28.2	4.0	23.1
2004	40.5	32.7	2.6	24.1
2005	41.8	30.0	2.0	26.1
2006	42.0	30.1	1.6	26.3
2007	50.8	21.1	1.4	26.6
2011	61.2	15.0	0.8	23.0
2012	58.1	16.2	1.0	24.7
2013	59.7	18.2	0.4	21.6
Total	45.8	40.1	5.9	24.0

seems to stop or even reverse starting from year 2011. More detailed break down can be found in table 3.3. The SOE category in Figure 3.7 contains the SOE and COE in table 3.3, while the non-SOE category contains the other two, POE stands for private owned firms, and FOE for foreign investor owned firms.

In table 3.4 and table 3.5 show respectively the share of labor by different ownership and the share of value added by different ownership. Both tables show a similar pattern to table 3.3. All three tables reveal the same signal: by any type size measure (share of capital, labor employment or value added), the SOEs have experienced a significant share drop in the economy due to the privatization process. However, the process slows down starting from 2011, which coincides with the timing of TFP drop.

In Figure 3.8, we show the average interest rate by SOE categories. The average interest

Table 3.4: Summary Statistics Labor by Ownership

	Ownership			
year	**POE**	**SOE**	**COE**	**FOE**
	%	%	%	%
1998	16.2	52.8	19.8	11.2
1999	19.3	48.5	18.8	13.4
2000	24.5	42.5	17.1	15.9
2001	37.1	31.8	13.8	17.4
2002	41.2	28.0	11.9	18.9
2003	45.0	23.1	9.7	22.2
2004	49.2	19.4	5.5	25.9
2005	50.5	17.2	5.0	27.4
2006	52.1	15.6	4.0	28.3
2007	55.6	12.0	3.4	29.0
2011	61.4	6.6	1.3	30.7
2012	61.4	6.5	1.3	30.8
2013	64.2	6.3	1.2	28.2
Total	50.5	33.4	13.0	24.6

Table 3.5: Summary Statistics Value Added by Ownership

	Ownership			
year	**POE**	**SOE**	**COE**	**FOE**
	%	%	%	%
1998	18.0	43.1	16.7	22.2
1999	21.1	37.5	14.8	26.7
2000	28.8	29.6	11.9	29.7
2001	44.3	20.9	7.8	27.0
2002	45.9	20.4	6.9	26.9
2003	45.6	19.1	5.5	29.8
2004	37.9	26.7	3.3	32.2
2005	40.1	27.1	3.4	29.5
2006	41.9	26.0	2.9	29.2
2007	55.3	13.1	2.4	29.3
2011	62.5	8.8	1.1	27.6
2012	64.0	7.9	1.1	27.0
2013	65.1	7.9	0.6	26.4
Total	47.9	28.0	9.3	28.4

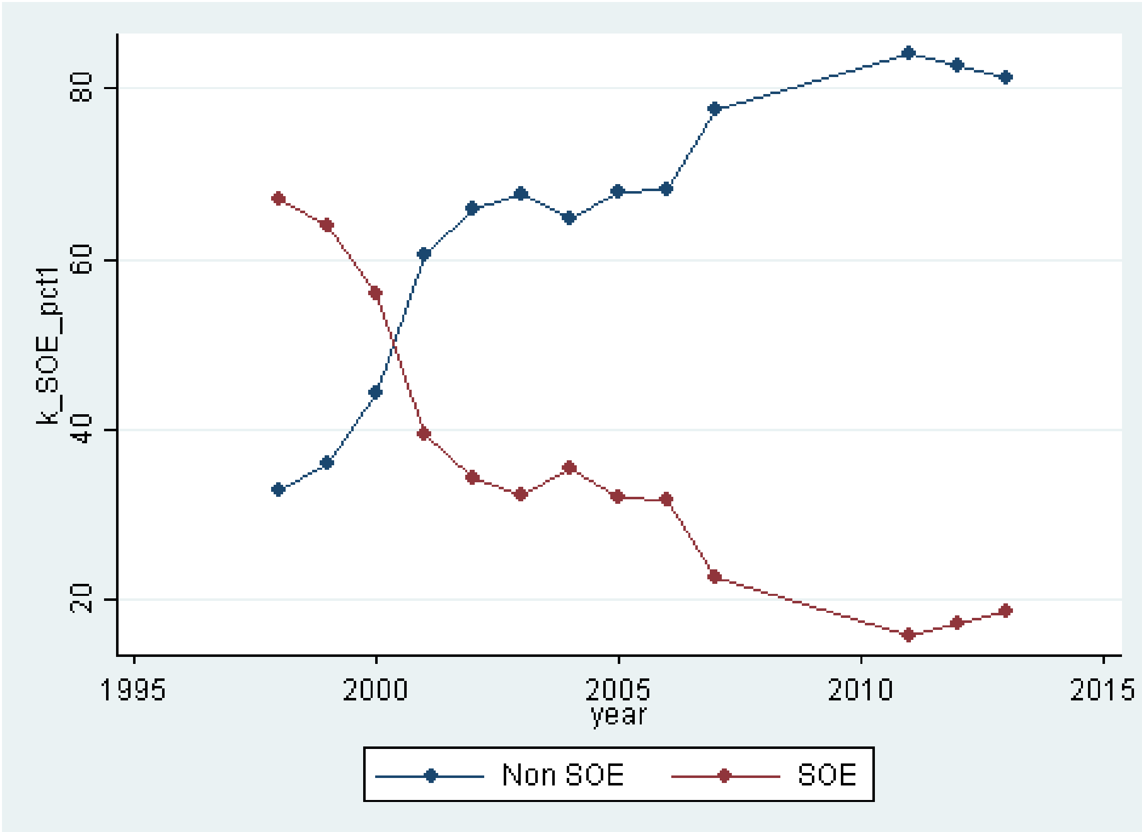


Figure 3.7: Shares of by SOE category

rate is measured as the interest expense over the debt. And in Figure 3.8 we only include the interest rate between 0 and 1. We can see the borrowing cost of SOEs are much lower than POEs. In all the years of the data set, the average interest rate of SOEs are below 4%, while most of the years, the average interest rate of POEs are above 4% and but below 6%. After 2004, the difference between the average interest rate is even widening between the SOEs and POEs.

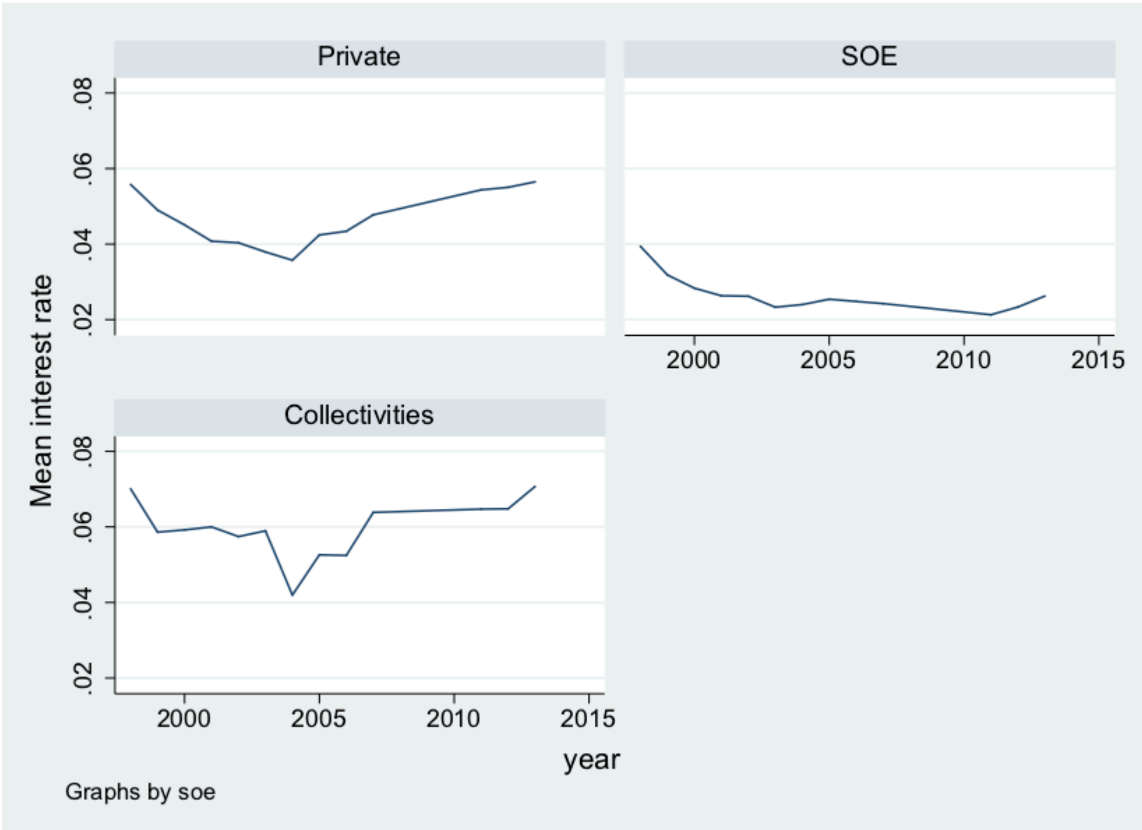


Figure 3.8: Interests by SOE category

3.5 Compositional Transition Between SOEs and Non-SOEs

In this section, we attempt to decompose the contributions of SOEs and Non-SOEs to aggregate TFP dynamics. We present evidence showing that in the early period (1998 - 2011), the TFP increase is mainly due to the within Non-SOEs TFP growth; while in the late period (2011 - 2013), the TFP decrease is mainly related to the within SOE TFP decline. The reallocation between SOEs and non-SOEs also plays a role in explaining the change of the TFP growth path of the two periods. With more detailed decomposition within SOEs and non-SOEs, there is a within firm TFP growth flip in SOEs, but not in non-SOEs.

We now describe the decomposition. First, we start with the definition of total production as the sum of real value added by each firm, which we assume to be the product of Cobb-Douglas production function.

$$Y_t = \Sigma A_{it} k_{it}^{\alpha} l_{it}^{\beta} \tag{3.12}$$

Moreover, to understand the connection between firm-level dynamics and a standard measure of aggregate TFP, we define aggregate TFP as the Solow residual of an aggregate production function with aggregate inputs K_t and L_t. That is, the aggregate TFP measure can be expressed as follows:

$$\begin{aligned}
\text{TFP}_t \equiv A_t = \tfrac{Y_t}{K^{\alpha} L^{\beta}} &= \Sigma_i A_{it} \tfrac{k_{it}^{\alpha} l_{it}^{\beta}}{K_t^{\alpha} L_t^{\beta}} \\
&= \Sigma_s \tfrac{\Sigma_{i \in s} k_{it}^{\alpha} l_{it}^{\beta}}{K_t^{\alpha} L_t^{\beta}} \underbrace{\Sigma_{i \in s} \frac{k_{it}^{\alpha} l_{it}^{\beta}}{\Sigma_{i \in s} k_{it}^{\alpha} l_{it}^{\beta}} A_{it}}_{\equiv TFP_t^s} \qquad (3.13) \\
&= \Sigma_s \tfrac{\Sigma_{i \in s} k_{it}^{\alpha} l_{it}^{\beta}}{K_t^{\alpha} L_t^{\beta}} TFP_t^s
\end{aligned}$$

where s is the subscript for the SOE/non-SOE categories and is the firm identifier. The expression above therefore links firm-level TFP measures to the aggregate measure. In particular, the aggregate TFP measure is simply a weighted average of SOE and Non-SOE TFP respectively, with the weights of each firm category given by $\Sigma_i \frac{k_{it}^{\alpha} l_{it}^{\beta}}{\Sigma_{i \in s} k_{it}^{\alpha} l_{it}^{\beta}} A_{it}$.

Using this construct, we can also decompose the change in aggregate TFP between two years into three parts as shown in equation 3.14: changes within SOE categories, changes between SOE/non-SOE (driven by changes in privatization trends) and a covariance term.

$$\Delta TFP_t^* \equiv \underbrace{\Sigma_s \frac{\Sigma_{i\in s} k_{ir}^{\alpha} l_{ir}^{\beta}}{K_r^{\alpha} L_r^{\beta}} \Sigma_{i\in s} \frac{k_{ir}^{\alpha} l_{ir}^{\beta}}{\Sigma_{i\in s} k_{ir}^{\alpha} l_{ir}^{\beta}} A_{ir}}_{\text{TFP}_r} - \underbrace{\Sigma_s \frac{\Sigma_{i\in s} k_{it}^{\alpha} l_{it}^{\beta}}{K_t^{\alpha} L_t^{\beta}} \Sigma_{i\in s} \frac{k_{it}^{\alpha} l_{it}^{\beta}}{\Sigma_{i\in s} k_{it}^{\alpha} l_{it}^{\beta}} A_{it}}_{\text{TFP}_t}$$

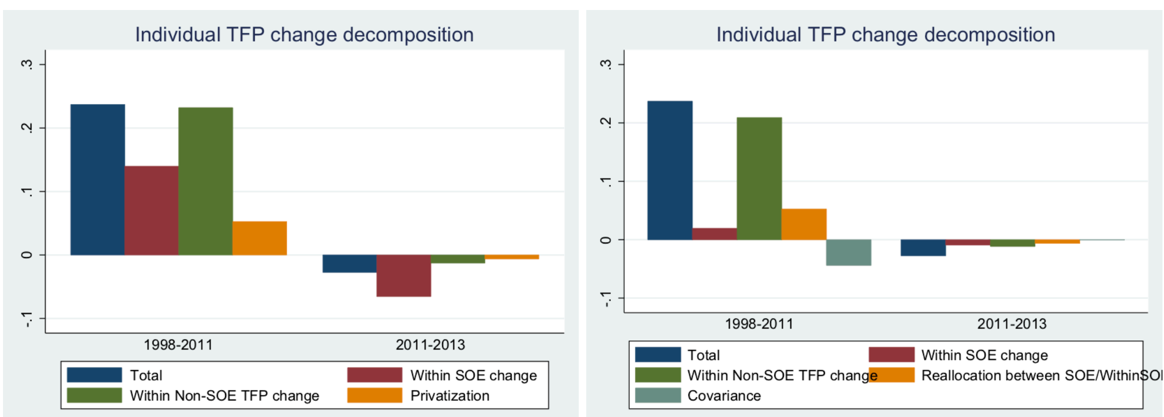
$$= \underbrace{\Sigma_s \frac{\Sigma_{i\in s} k_{ir}^{\alpha} l_{ir}^{\beta}}{K_r^{\alpha} L_r^{\beta}} [TFP_r^S - TFP_t^S]}_{\text{Within SOE/non-SOE changes}} + \underbrace{\Sigma_s [\frac{\Sigma_{i\in s} k_{ir}^{\alpha} l_{ir}^{\beta}}{K_r^{\alpha} L_r^{\beta}} - \frac{\Sigma_{i\in s} k_{it}^{\alpha} l_{it}^{\beta}}{K_t^{\alpha} L_t^{\beta}}] TFP_r^S}_{\text{Privatization}} \qquad (3.14)$$

$$\underbrace{-\Sigma_s (TFP_r^S - TFP_t^S)(\frac{\Sigma_{i\in s} k_{ir}^{\alpha} l_{ir}^{\beta}}{K_r^{\alpha} L_r^{\beta}} - \frac{\Sigma_{i\in s} k_{it}^{\alpha} l_{it}^{\beta}}{K_t^{\alpha} L_t^{\beta}})}_{\text{Covariance term}}$$

where r is the reference year, which we set to 2011, and t is the year in question. We perform TFP growth decomposition for the 1998-2011 and between 2011–2013 separately.

The result of the decomposition in equation 3.14 is presented in 3.9a. The results are presentend with and without sector weights ($\Sigma_i \frac{k_{it}^{\alpha} l_{it}^{\beta}}{\Sigma_{i\in s} k_{it}^{\alpha} l_{it}^{\beta}} A_{it}$.). There are several features worth noting in the unweighted results. First, there is a shift from positive to negative contributions to aggregate TFP growth in both the within Non-SOE component (green) and the within SOE component (red). Second, the contribution in the second period is more negative in the SOE component than in the non SOE component. Third, movements of capital and labor away from SOEs and into SOEs also had positive effects during the period, though these contribution only accounts for a small share of the total aggregate TFP growth in TFP. Fourth, mirroring the privatization slow-down, the component switched from positive to negative in the later sub-period.

Because there is a significant movement away from SOEs in this period, weighted results assessing the quantitative impact of SOE growth depend on the year of reference weights used. Since 2011 weights are used, this understates the quantitative impact of SOE changes and overstates the impact of SOE changes. Using the labeling of 2011, we can see that most of the contribution to TFP growth was driven by firms that were not SOEs in 2011, as well as by the privatization efforts leading to 2011. Consistent with the unweighted results, the contribution of these forces reversed in the period between 2011-2013.



(a) Unweighted between-within SOE TFP Changes (b) Weighted between-within SOE TFP Changes

Figure 3.9: TFP Changes by SOE Category

The exercise above motivates our study of changes within the SOE and Non-SOE TFP component. Each of these components can be further decomposed into five subcomponents: within firm changes in TFP, reallocation of capital and labor between firms within each SOE/Non-SOE category, entry and exit, and covariance between within firm TFP changes and the reallocation of capital and labor. The decomposition method is expressed in equation 3.15.

$$\Delta TFP_t^S \equiv TFP_r^s - TFP_t^s$$

$$= \Sigma_{i\in s}\frac{k_{ir}^{\alpha}l_{ir}^{\beta}}{\Sigma_{i\in s}k_{ir}^{\alpha}l_{ir}^{\beta}}A_{ir} - \Sigma_{i\in s}\frac{k_{it}^{\alpha}l_{it}^{\beta}}{\Sigma_{i\in s}k_{it}^{\alpha}l_{it}^{\beta}}A_{it}$$

$$= \underbrace{Weight_{stay^s,r}\Sigma_{i\in stay^s}\frac{k_{ir}^{\alpha}l_{ir}^{\beta}}{\Sigma_{i\in stay^s}k_{ir}^{\alpha}l_{ir}^{\beta}}[A_{ir} - A_{it}]}_{\text{Within Firm}}$$

$$\underbrace{+Weight_{stay^s,r}\Sigma_{i\in stay^s}[\frac{k_{ir}^{\alpha}l_{ir}^{\beta}}{\Sigma_{i\in stay^s}k_{ir}^{\alpha}l_{ir}^{\beta}} - \frac{Weight_{stay^s,t}}{Weight_{stay^s,r}}\frac{k_{it}^{\alpha}l_{it}^{\beta}}{\Sigma_{i\in stay^s}k_{it}^{\alpha}l_{it}^{\beta}}]A_{it}}_{\text{Between Firm}}$$

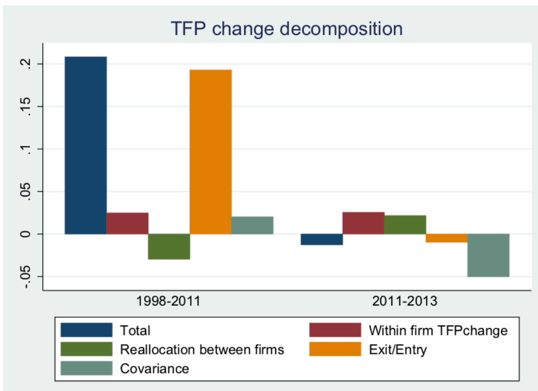
$$\underbrace{+Weight_{enter^s,r}\Sigma_{i\in enter^s}\frac{k_{ir}^{\alpha}l_{ir}^{\beta}}{\Sigma_{i\in enter^s}k_{ir}^{\alpha}l_{ir}^{\beta}}A_{ir}}_{\text{Enry}} - \underbrace{Weight_{exit^s,t}\Sigma_{i\in exit^s}\frac{k_{it}^{\alpha}l_{it}^{\beta}}{\Sigma_{i\in exit^s}k_{it}^{\alpha}l_{it}^{\beta}}A_{it}}_{\text{Exit}}$$

$$\underbrace{-\Sigma_{i\in stay^s}(A_{ir} - A_{it})(\frac{k_{ir}^{\alpha}l_{ir}^{\beta}}{\Sigma_{i\in s}k_{ir}^{\alpha}l_{ir}^{\beta}} - \frac{k_{it}^{\alpha}l_{it}^{\beta}}{\Sigma_{i\in s}k_{it}^{\alpha}l_{it}^{\beta}})}_{\text{Covariance}} \tag{3.15}$$

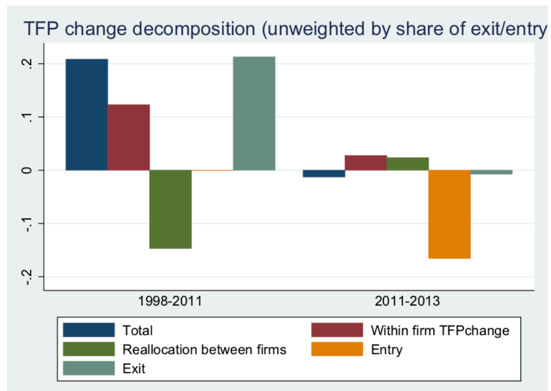
where $stay^s$ is the subset of s, standing for firms that exist both in year t and in reference year r in the category s; $enter^s$ is the subset of s, standing for firms that newly enter into the market in reference year r and do not exist in year t in the category s; $exit^s$ is the subset of s, standing for firms that exit in year t but do not exit in reference year r in the category s. Moreover,

$$\begin{aligned}
Weight_{stay^s,r} &\equiv \frac{\Sigma_{i \in stay^s} k_{ir}^{\alpha} l_{ir}^{\beta}}{\Sigma_{i \in s} k_{ir}^{\alpha} l_{ir}^{\beta}} \\
Weight_{stay^s,t} &\equiv \frac{\Sigma_{i \in stay^s} k_{it}^{\alpha} l_{it}^{\beta}}{\Sigma_{i \in s} k_{it}^{\alpha} l_{it}^{\beta}} \\
Weight_{enter^s,r} &\equiv \frac{\Sigma_{i \in enter^s} k_{ir}^{\alpha} l_{ir}^{\beta}}{\Sigma_{i \in s} k_{ir}^{\alpha} l_{ir}^{\beta}} \\
Weight_{exit^s,t} &\equiv \frac{\Sigma_{i \in exit^s} k_{it}^{\alpha} l_{it}^{\beta}}{\Sigma_{i \in s} k_{it}^{\alpha} l_{it}^{\beta}}
\end{aligned} \tag{3.16}$$

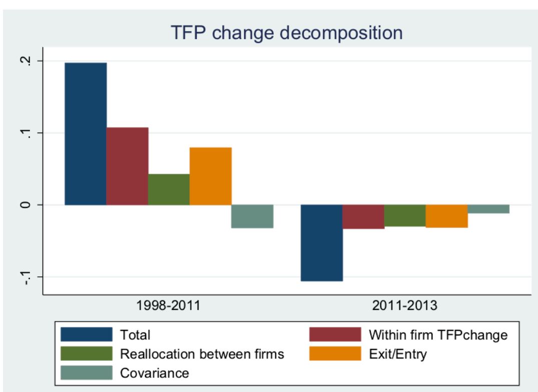
The result of the decomposition described in equation 3.15 is shown in Figure 3.10. The first row is the weighted and unweighted within non-SOE TFP change while the second row is the counterpart for the SOE TFP change. The first column is the weighted TFP change while the second column is the unweighted TFP change. One interesting pattern is that for SOEs, the within firm TFP change (maroon bar) flips from positive in the first sub-period to negative in the second sub-period, while we do not observe the same change in non-SOEs. This means that on average the measured TFP experience a decline for the existing SOEs but not for the existing non-SOEs. Anther point is that the reallocation between firms (green bar) causes a TFP growth flip in SOEs but not in non-SOEs, indicating that SOEs may suffer more misallocation in the second sub-period compared to the non-SOEs.



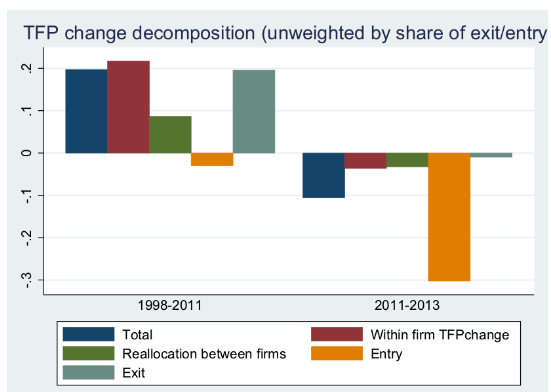
(a) Weighted within non-SOE TFP Changes



(b) Unweighted within non-SOE TFP Changes



(c) Weighted within SOE TFP Changes



(d) Unweighted within SOE TFP Changes

Figure 3.10: TFP Changes by within SOE/Non-SOE

Table 3.6: Correlations between changes in TFP and changes in capacity utilization

	All	1998–2007	2008–2013	1998–2011	2012–2013
	D.lnTFP	D.lnTFP	D.lnTFP	D.lnTFP	D.lnTFP
D.Utilization	0.00144	0.00178	-0.0357	0.00178	-0.0357
	(0.00171)	(0.00144)	(0.0285)	(0.00144)	(0.0285)
Constant	0.0907**	0.0969**	0.0464	0.0969**	0.0464
	(0.0435)	(0.0388)	(0.212)	(0.0388)	(0.212)
Observations	72	63	9	63	9
R-squared	0.010	0.025	0.183	0.025	0.183

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.6 TFP trends and capacity dynamics

An alternative explanation for the patterns documented is that these are driven by capacity utilization dynamics. This is certainly a possibility since, our measures of TFP, can are affected by capacity utilization changes. In particular, the slow-down of TFP might be the product of lagging capacity utilization.

To assess this potential challenge, we gathered data from Chinese Statistical Year Book on capacity and production for available manufacturing sectors. A utilization variable was constructed by dividing total production in that sector by the capacity measure. Sectors with enough observations before and after 2008 were selected. Figure 3.11 present the trends in average TFP and industry-level capacity for industries with available data and table 3.6 documents the correlation between changes in utilization and mean TFP at the sectoral level. We find no evidence of strong correlation between changes in TFP and changes in measured capacity utilization. Moreover, from the limited available evidence, we find no evidence of a decrease in capacity utilization that could explain the deceleration in TFP.

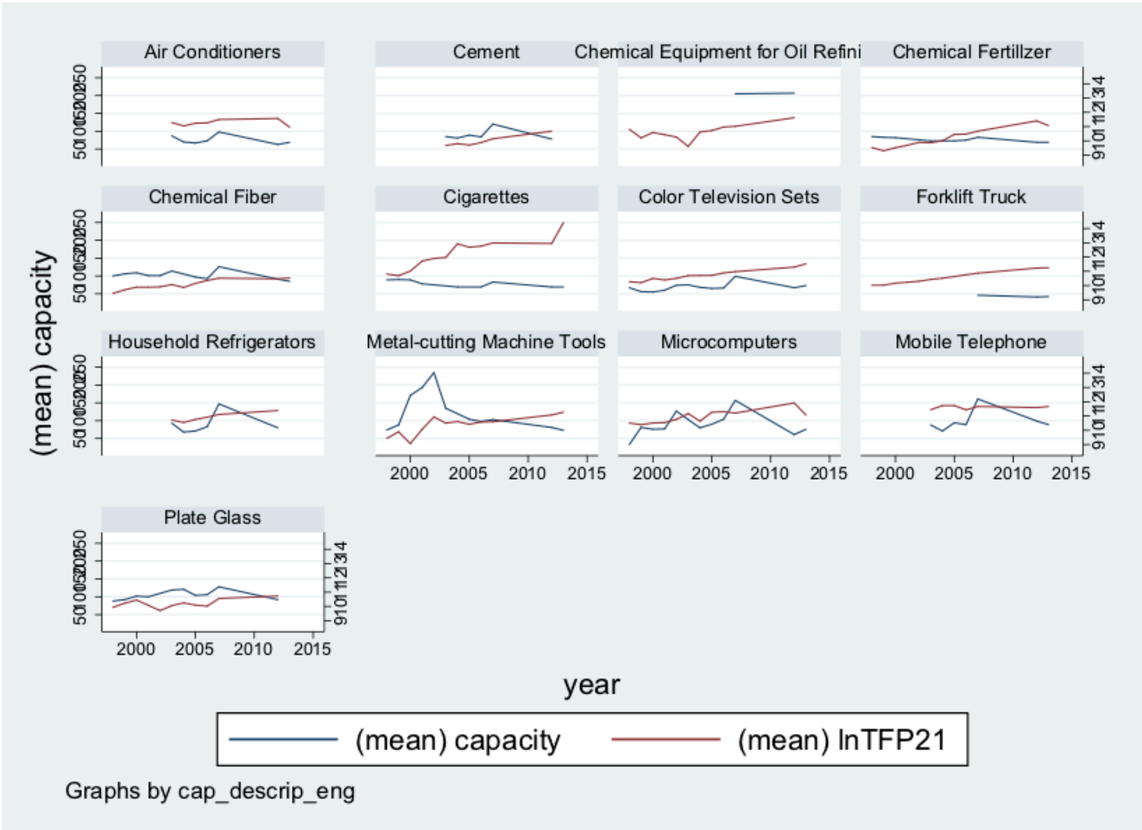


Figure 3.11: Trends in capacity utilization and TFP by industry

3.7 Conclusion

After a decade of growth, manufacturing TFP measured from both and aggregate and micro perspective seems to have decelerated in China after 2007. When decomposing this changes, within-firm TFP changes among SOEs and privatization, which were drivers of growth before 2007, seem to have reversed in the years after 2011. In particular, earlier lags in productivity in SOEs when compared to POEs seem to have shrunk, suggesting that an past avenue of growth might have been exhausted.

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Appendices

1. Primal Measure and Dual Measure of TFP

The derivation in this subsection is an extension of Hsieh 2002.

Assume the market is perfectly competitive. The sector s's output at time t Y_{st}, should be equal to the payment to the factors of the production, say capital and labor for the purpose of illustration:

$$Y_{st} = r_{st}K_{st} + w_{st}L_{st} \tag{17}$$

where K_{st} and L_{st} are respectively the capital stock and labor employment, and r_{st} and w_{st} are the rental price of capital and the wage.

Take the total derivative of the equation above with respect to time and divide it by Y_{st}:

$$\frac{dY_{st}}{Y_{st}} = \frac{K_{st}dr_{st}}{Y_{st}} + \frac{dK_{st}r_{st}}{Y_{st}} + \frac{L_{st}dw_{st}}{Y_{st}} + \frac{dL_{st}w_{st}}{Y_{st}} \tag{18}$$

Change the previous equation by making the labor share and the capital share appear:

$$\frac{dY_{st}}{Y_{st}} = \frac{K_{st}r_{st}}{Y_{st}}\frac{dr_{st}}{r_{st}} + \frac{K_{st}r_{st}}{Y_{st}}\frac{dK_{st}}{K_{st}} + \frac{L_{st}w_{st}}{Y_{st}}\frac{dw_{st}}{w_{st}} + \frac{L_{st}w_{st}}{Y_{st}}\frac{dL_{st}}{L_{st}} \tag{19}$$

The discrete time counterpart is to replace operator d by Δ:

$$\tfrac{\Delta Y_{st}}{Y_{st}} = \tfrac{K_{st}r_{st}}{Y_{st}}\tfrac{\Delta r_{st}}{r_{st}} + \tfrac{K_{st}r_{st}}{Y_{st}}\tfrac{\Delta K_{st}}{K_{st}} + \tfrac{L_{st}w_{st}}{Y_{st}}\tfrac{\Delta w_{st}}{w_{st}} + \tfrac{L_{st}w_{st}}{Y_{st}}\tfrac{\Delta L_{st}}{L_{st}}.$$

Let s^K_{st} denote the capital share and s^L_{st} the labor share. By definition, $s^K_{st} = \frac{K_{st}r_{st}}{Y_{st}}$ and $s^L_{st} = \frac{L_{st}w_{st}}{Y_{st}}$. Moreover, $\frac{dx}{x}$ is the growth rate of variable x, denoted as $\hat{x}$.

Then, the previous equation can be written as follows after rearrangement of terms:

$$\underbrace{\hat{Y}_{st} - s^K_{st}\hat{K} - s^L_{st}\hat{L}_{st}}_{\text{Primal: } \hat{A}^P_{st}} = \underbrace{s^K_{st}\hat{r}_{st} + s^L_{st}\hat{w}_{st}}_{\text{Dual: } \hat{A}^D_{st}} \tag{20}$$

The left-hand side is the primal measure used in KLEMS data, and the right-hand side is the dual measure. The derivation only depends on one single assumption of market competitiveness without any other assumption such as the form of the production function.

If the production is Cobb-Douglas $Y_{st} = A_{st}K^{\alpha}_{st}L^{1-\alpha}_{st}$, then $s^K = \alpha$, $s^L = 1 - \alpha$.

It is very straightforward to extend the dual measure to more than two input factors: $\hat{A}^D_{st} = \Sigma^n_{j=1}s^j_{st}\hat{r}^j_{st}$, where $\hat{r}^j_{st}$ is the growth rate of the price of input j and s^j_{st} is its share.

It should be noticed that the theoretical equivalence between the primal measure and is also true with more general CES production function.

Suppose $Y_{st} = A_{st}(\alpha K_{st}^{\frac{\rho-1}{\rho}} + (1-\alpha)L_{st}^{\frac{\rho-1}{\rho}})^{\frac{\rho}{\rho-1}}$, where ρ is the elasticity of substitution. The Cobb-Douglas function is a special case, where the elasticity of substitution is $\rho = 1$. This can be shown by using the l'Hopitale's rule.

Still under the assumption that the market is competitive:

$$
\begin{aligned}
r_{st} &= \tfrac{\partial Y_{st}}{\partial K_{st}} = A_{st}\alpha K_{st}^{\frac{\rho-1}{\rho}-1}(\alpha K_{st}^{\frac{\rho-1}{\rho}} + (1-\alpha)L_{st}^{\frac{\rho-1}{\rho}})^{\frac{\rho}{\rho-1}-1} \\
w_{st} &= \tfrac{\partial Y_{st}}{\partial L_{st}} = A_{st}(1-\alpha)L_{st}^{\frac{\rho-1}{\rho}-1}(\alpha K_{st}^{\frac{\rho-1}{\rho}} + (1-\alpha)L_{st}^{\frac{\rho-1}{\rho}})^{\frac{\rho}{\rho-1}-1}
\end{aligned}
\tag{21}
$$

Denote $s_{st}^K = \frac{r_{st}K_{st}}{Y_{st}} = \frac{\alpha K_{st}^{\frac{\rho-1}{\rho}}}{\alpha K_{st}^{\frac{\rho-1}{\rho}} + (1-\alpha)L_{st}^{\frac{\rho-1}{\rho}}}$,
and $s_{st}^L = \frac{r_{st}K_{st}}{Y_{st}} = \frac{(1-\alpha)L_{st}^{\frac{\rho-1}{\rho}}}{\alpha K_{st}^{\frac{\rho-1}{\rho}} + (1-\alpha)L_{st}^{\frac{\rho-1}{\rho}}}$.

The difference between the general CES function and Cobb-Douglas function is that the labor share and capital share now depend on capital stock and employment.

Without the the assumption of perfect competition, then the output is divided into three parts, labor share, capital share and profit:

$$
Y_{st} = r_{st}K_{st} + w_{st}L_{st} + \pi_{st} \tag{22}
$$

where π_{st} is the profit of sector s at time t.

Performing a similar operation on the previous equation, we get:

$$
\hat{Y}_{st} - s_{st}^K\hat{K}_{st} - s_{st}^L\hat{L}_{st} = s_{st}^K\hat{r}_{st} + s_{st}^L\hat{w}_{st} + s_{st}^\pi\hat{\pi}_{st} \tag{23}
$$

Replace $s^K_{st} = 1 - s^L_{st} - s^\pi_{st}$ in the previous equation:

$$\hat{Y}_{st} - (1 - s^L_{st} - s^\pi_{st})\hat{K}_{st} - s^L_{st}\hat{L}_{st} = (1 - s^L_{st} - s^\pi_{st})\hat{r}_{st} + s^L_{st}\hat{w}_{st} + s^\pi_{st}\hat{\pi}_{st} \tag{24}$$

After rearranging the terms,

$$\hat{Y}_{st} - (1 - s^L_{st})\hat{K}_{st} - s^L_{st}\hat{L}_{st} = (1 - s^L_{st})\hat{r}_{st} + s^L_{st}\hat{w}_{st} + s^\pi_{st}(\hat{\pi}_{st} - \hat{K}_{st} - \hat{r}_{st}) \tag{25}$$

Since $\hat{\pi}_{st} - \hat{K}_{st} - \hat{r}_{st} = \hat{\pi}_{st} - \widehat{r_{st}K}_{st} = \hat{\pi}_{st} - \hat{Y}_{st} - (\widehat{r_{st}K}_{st} - \hat{Y}_{st}) = \hat{s}^\pi_{st} - \hat{s}^K_{st}$,

the previous equation can be rewritten as:

$$\underbrace{\hat{Y}_{st} - (1 - s^L_{st})\hat{K}_{st} - s^L_{st}\hat{L}_{st}}_{\text{Primal: } \hat{A}^P_{st}} = \underbrace{(1 - s^L_{st})\hat{r}_{st} + s^L_{st}\hat{w}_{st}}_{\text{Dual: } \hat{A}^D_{st}} + s^\pi_{st}(\hat{s}^\pi_{st} - \hat{s}^K_{st}) \tag{26}$$

Even with the true condition not being perfect competition, we can still calculate the primal measure and dual measure of TFP growth. However, the previous equation shows that it is no longer true that the primal measure equals the dual measure: the former exceeds the latter by $s^\pi_{st}(\hat{s}^\pi_{st} - \hat{s}^K_{st})$.

How is the dual measure computed in the data? Here are the steps:

- Compensation of Labor $Comp_L$: directly observed
- Labor L: directly observed, total hours or total employees
- Labor share $s_L = \frac{Comp_L}{Y}$

- Nominal wage $w^n = \frac{Comp_L}{L}$
- Real wage growth $\hat{w} = \hat{w}^n - \pi$, π GDP-deflator inflation (Source: WDI)
- Compensation of Capital $Comp_K = Y - Comp_L$
- Capital share: $s_K = \frac{Comp_K}{Y}$
- Capital Stock K: Estimated by perpetual inventory model
- Nominal rental price: r^n from KLEMS data, and real rental price $\hat{r} = \hat{r}^n - \pi$.
- Real rental price growth $\hat{r} = \hat{r}^n - \pi$

2. Amadeus Spain Summary Statistics

Following Kalemli-Ozcan et al. 2015, the data are downloaded from four vintage discs of AMADEUS[6] (June 2000, June 2003, June 2006, and December 2009) to deal with the issues of download cap and missing records.[7] From each disk, last five observations are downloaded, which are not necessarily the last five years. For example, in 2006 dataset, the last five observations could be 2005, 2004, 2003, 2002, and 2000. The missing 2001 data may be due to the facto that there is no report. Before merging the data from different vintage disks, I update the BVD ID of the firms that had BVD ID change between 1999 and 2009 to their BVD ID number in 2009, following the information downloaded from website idchanges.bvdinfo.com.[8] The updated BVD ID number then serves as the unique identifier to merge the firms. After merging the data using the BVD ID number, I then drop all the duplicates and drop all the consolidated firms. Some summary statistics are listed here.

[6]AMADEUS is a product by Bureau van Dijk. Unlike the ORBIS dataset, which provides firm-level data for companies around the world, AMADEUS focuses on European countries.

[7]Kalemli-Ozcan et al. 2015 documents that if someone tries to download a lot of data at one time, the download cap will translate into missing information of the downloaded data. It is also documented in their paper that if a firms does not report anything in the last 5 years, it would be excluded even if it is still in operation.

[8]This is the website that stores the history of BVD ID changes for all firms in products of Bureau Van Dijk.

Table 1: Size Distribution of Spanish Firms in All Sectors

	YEAR	1 - 19	20 - 249	>=250	Total
Full Sample	1999	64539	34951	1595	101085
	2000	93653	41902	1869	137424
	2001	124955	47166	2109	174230
	2002	170876	51343	2134	224353
	2003	285163	56363	2239	343765
	2004	406743	60387	2290	469420
	2005	461818	63904	2339	528061
	2006	496480	67471	2442	566393
	2007	457458	65859	2484	525801
	Total	2561685	489346	19501	3070532
Half Sample	1999	52540	29828	1206	83574
	2000	77971	36700	1495	116166
	2001	89330	42004	1739	133073
	2002	94877	46531	1895	143303
	2003	100290	50257	2041	152588
	2004	103077	52674	2131	157882
	2005	102434	53470	2145	158049
	2006	100743	54002	2180	156925
	2007	94579	51535	2198	148312
	Total	815841	417001	17030	1249872
Stayers Sample	1999	19775	11048	433	31256
	2000	20502	12803	505	33810
	2001	20858	13939	565	35362
	2002	21223	14972	604	36799
	2003	21433	15572	632	37637
	2004	21666	15973	647	38286
	2005	22000	16232	697	38929
	2006	22077	16602	733	39412
	2007	22109	16715	780	39604
	Total	191643	133856	5596	331095

Source: Amadeus Spain

In the permanent sample, the change of the numbers of firms in each category is mainly because of data availability, meaning in 2007 more labor data of firms are observed compared to 1999.

Table 2: Number of Firms in All Sectors in Spain

	YEAR	SectorA	SectorB	SectorC	SectorD	SectorE	SectorF	SectorG	SectorH	SectorI	SectorJ	SectorK	Sector r	Total
Full Sample	1999	2158	346	915	33692	681	17696	50444	4625	8157	741	21060	5177	145692
	2000	2676	417	1094	38072	894	24178	59586	6171	10023	966	30375	6772	181224
	2001	3979	531	1236	42958	1062	30725	70497	9123	11857	1445	43488	9419	226320
	2002	6187	678	1364	49336	1385	40089	84810	13820	14695	2504	71215	14671	300754
	2003	10837	938	1843	70607	2034	66222	122065	22648	21282	5034	129891	24259	477660
	2004	14945	1236	2307	92508	2698	92571	160212	31728	28283	6561	180876	33380	647305
	2005	16675	1304	2461	98099	3346	106416	175378	36529	30976	7642	211653	37804	728283
	2006	17092	1402	2486	100231	5385	117408	181437	39693	31974	8205	232591	40198	778102
	2007	14218	1250	2218	92457	5921	109082	164805	34955	28981	6760	196745	33950	691342
	Total	88767	8102	15924	617960	23406	604387	1069234	199292	186228	39858	1117894	205630	4176682
Half Sample	1999	1623	297	802	28545	538	14547	42552	3697	6604	379	14024	3752	117360
	2000	1948	344	971	32739	708	20230	50918	4808	8271	492	20711	4932	147072
	2001	2242	380	1027	34416	776	22840	55303	5537	8955	527	23454	5502	160959
	2002	2366	388	1037	35010	823	23942	57078	5880	9349	531	24565	5845	166814
	2003	2760	402	1092	37305	872	25924	59765	6259	9890	564	26920	6096	177849
	2004	3049	453	1116	39164	916	26940	61019	6418	10240	574	28588	6193	184670
	2005	3020	448	1103	38463	893	26719	60396	6350	10055	541	28247	6143	182378
	2006	2979	431	1081	37788	872	26315	59415	6270	9876	535	27492	6024	179078
	2007	2758	394	1007	35467	797	24665	55771	5844	9173	502	25209	5521	167108
	Total	22745	3537	9236	318897	7195	212122	502217	51063	82413	4645	219210	50008	1483288
Stayers Sample	1999	541	117	285	11202	162	5103	16462	1183	2339	57	3611	1161	42223
	2000	465	98	271	10518	158	4873	15565	1156	2243	53	3453	1135	39988
	2001	465	98	271	10518	159	4875	15550	1156	2241	52	3454	1135	39974
	2002	465	98	271	10518	159	4875	15550	1156	2241	52	3454	1135	39974
	2003	465	98	271	10518	159	4875	15550	1156	2241	52	3454	1135	39974
	2004	593	120	298	11445	182	5147	15914	1219	2395	55	3832	1143	42343
	2005	593	120	298	11446	182	5147	15913	1219	2395	55	3833	1143	42344
	2006	593	120	298	11446	182	5147	15913	1219	2395	55	3833	1143	42344
	2007	593	120	298	11446	182	5147	15913	1219	2395	55	3833	1143	42344
	Total	4773	989	2561	99057	1525	45189	142330	10683	20885	486	32757	10273	371508

Raw data: Amadeus Spain

The main three sectors used in the paper are: SectorD, SectorF and SectorK, which are respectively the manufacturing sector, the construction sector and the real estate sector. The other sectors are: SectorA, agriculture; SectorB, fishing; SectorC, mining; SectorE, utility; SectorG, wholesale and retail; SectorH, hotels and restaurants; SectorI, transport; SectorJ, financial intermediation; Sector r, others including education, community social service, public administration etc.

3. Derivation of Price Index and Demand

Using the cost minimization method, we can back out the price of consumption goods in terms of the prices of tradable and non-tradable goods:

$$\min_{C_t^T, C_t^N} p_t^T C_t^T + p_t^N C_t^N$$

$$\text{s.t. } [\gamma(C_t^T)^{1-\frac{1}{\xi}} + (1-\gamma)(C_t^N)^{1-\frac{1}{\xi}}]^{\frac{\xi}{\xi-1}} = C_t$$

By solving this problem, we get $C_t^N = \frac{C_t(\frac{p_t^N}{1-\gamma})^{-\xi}}{[\gamma^\xi(p_t^T)^{1-\xi}+(1-\gamma)^\xi(p_t^N)^{1-\xi}]^{\frac{\xi}{\xi-1}}}$□

and $C_t^T = \frac{C_t(\frac{p_t^T}{\gamma})^{-\xi}}{[\gamma^\xi(p_t^T)^{1-\xi}+(1-\gamma)^\xi(p_t^N)^{1-\xi}]^{\frac{\xi}{\xi-1}}}$.

Moreover, the price index of the consumption goods

$p_t \equiv \frac{p_t^T C_t^T + p_t^N C_t^N}{C_t} = [\gamma^\xi(p_t^T)^{1-\xi} + (1-\gamma)^\xi(p_t^N)^{1-\xi}]^{\frac{1}{1-\xi}}$.

Therefore, we get $C_t^N = C_t(\frac{p_t^N}{p_t(1-\gamma)})^{-\xi}$, $C_t^T = C_t(\frac{p_t^T}{p_t\gamma})^{-\xi}$.

A special case is that when $\xi = 1$, the CES aggregator degenerates to a Cobb-Douglas aggregator, $C_t = (C_t^T)^\gamma(C_t^N)^{1-\gamma}$, and $p_t = \frac{(p_t^T)^\gamma((p_t^N)^{(1-\gamma)}}{\gamma^\gamma(1-\gamma)^{(1-\gamma)}}$, and the ratio of the non-tradable expenditure on total expenditure is constant, $C_t^N p_t^N = (1-\gamma)C_t p_t$.

4. Derivation of Loan and Deposit Equilibrium Condition

By definition, the loan from the bank to non-tradable firms is:

$B_t = \int_{a_t^*}^{\bar{a}} b_t dH(a_{t-1})$

$= \int_{a_{t-1}^*}^{\bar{a}} \theta x_t(a_{t-1}) k_{t-1} dH(a_{t-1})$, Since $b_t = \theta x_t(a_{t-1}) k_{t-1}$

$= \int_{a_{t-1}^*}^{\bar{a}} \theta x_t(a_{t-1}) \frac{\beta v_{t-1}}{1 - \frac{\theta x_t(a_{t-1})}{1+r_t^b}} dH(a_{t-1})$, Since $k_{t-1} = \frac{\beta v_{t-1}}{1 - \frac{\theta x_t(a_{t-1})}{1+r_t^b}}$

$= \frac{\theta\beta}{1-\theta} \int_{a_{t-1}^*}^{\bar{a}} v_{t-1} R_t(a_{t-1}) dH(a_{t-1})$, Since $R_t(a_{t-1}) = \frac{(1-\theta)x_t(a_{t-1})}{1 - \frac{\theta x_t(a_{t-1})}{1+r_t^b}}$

$= \frac{\theta\beta V_{t-1}}{1-\theta} \int_{a_{t-1}^*}^{\bar{a}} R_t(a_{t-1}) dH(a_{t-1})$, Since a_t is i.i.d

.

To see why a_t i.i.d can lead to the separation of the integration of the product of v_{t-1} and $R_t(a_{t-1})$, note that

$\int_{a_{t-1}^*}^{\bar{a}} v_{t-1} R_t(a_{t-1}) dH(a_{t-1}) = \underbrace{[\int_{\underline{a}}^{\bar{a}} dH(a_{t-1})]}_{=1} \int_{a_{t-1}^*}^{\bar{a}} v_{t-1} R_t(a_{t-1}) dH(a_t)$

$= \underbrace{[\int_{\underline{a}}^{\bar{a}} v_{t-1} dH(a_{t-1})]}_{V_{t-1}} \int_{a_{t-1}^*}^{\bar{a}} R_t(a_{t-1}) dH(a_{t-1}) = V_{t-1} \int_{a_{t-1}^*}^{\bar{a}} R_t(a_t) dH(a_t)$.

By definition, the deposit from the non-producing entrepreneurs is:

$D_t = \int_{\underline{a}}^{a_{t-1}^*} d_t dH(a_{t-1})$

$= \int_{\underline{a}}^{a_{t-1}^*} (1+r_t^d)(v_t - p_t c_t) dH(a_{t-1})$, Since non-producing entrepreneurs only consume and save

$= \int_{\underline{a}}^{a_{t-1}^*} \beta(1+r_t^d) v_{t-1} dH(a_{t-1})$

$= \beta(1+r_t^d) V_{t-1} H(a_{t-1}^*)$.

Combining the aggregate loan and aggregate deposit and equation 2.21, we can get rid of the aggregate wealth V_t and get:

$$(1 + r_t^d) H(a_{t-1}^*) = \frac{\theta(1 - \phi)}{1 - \theta} \int_{a_{t-1}^*}^{\bar{a}} R_t(a_{t-1}) dH(a_{t-1}) \tag{27}$$

Then we can get the expression of the integration:

$$\int_{a_{t-1}^*}^{\bar{a}} R_t(a_{t-1}) dH(a_{t-1}) = \frac{(1 + r_t^d)(1 - \theta) H(a_{t-1}^*)}{\theta(1 - \phi)} \tag{28}$$

5. Derivation of Labor Market Equilibrium Condition in the Non-tradable Sector

The law of motion of the aggregate wealth comes from the law of motion of the individual wealth, (i.e., equation 2.20).

By definition: $V_t = \int_{\underline{a}}^{\bar{a}} v_t dH(a_t)$

$= \int_{\underline{a}}^{\bar{a}} \beta[I(a_t > a_t^*)R_t(a_{t-1}) + (1 - I(a_{t-1} > a_{t-1}^*))(1 + r_t^d)]v_{t-1}dH(a_{t-1})$

$= \beta \int_{a_{t-1}^*}^{\bar{a}} v_{t-1}R_t(a_{t-1})dH(a_{t-1}) + \beta \int_{\underline{a}}^{a_{t-1}^*}(1 + r_t)v_{t-1}dH(a_{t-1})$

$= \beta V_{t-1} \underbrace{\int_{a_{t-1}^*}^{\bar{a}} R_t(a_{t-1})dH(a_{t-1})}_{=\frac{(1+r_t^d)(1-\theta)H(a_{t-1}^*)}{\theta(1-\phi)}} + \beta(1 + r_t^d)V_{t-1}H(a_{t-1}^*)$, Since a_t is i.i.d

$= \beta(1 + r_t^d)V_{t-1}H(a_{t-1}^*)\frac{1-\theta\phi}{\theta(1-\phi)}$

Labor demand in the non-tradable sector should be aggregated from the heterogeneous firms in this sector:

$L_t^N = \int_{a_{t-1}^*}^{\bar{a}} l_t dH(a_{t-1}) = \int_{a_{t-1}^*}^{\bar{a}} [\frac{(1-\alpha_N)p_t^N a_{t-1}}{\tilde{w}_t^N}]^{1/\alpha_N} k_{t-1}dH(a_{t-1})$

$= \int_{a_{t-1}^*}^{\bar{a}} [\frac{(1-\alpha_N)p_t^N a_{t-1}}{\tilde{w}_t^N}]^{1/\alpha_N} \frac{\beta v_{t-1}}{1-\frac{\theta x_t(a_{t-1})}{1+r_t^b}} dH(a_{t-1})$, Since $k_{t-1} = \frac{\beta v_{t-1}}{1-\frac{\theta x_t(a_{t-1})}{1+r_t^b}}$

$= \int_{a_{t-1}^*}^{\bar{a}} \frac{(1-\alpha_N)x_t(a_{t-1})}{\alpha_N \tilde{w}_t^N} \frac{\beta v_{t-1}}{1-\frac{\theta x_t(a_{t-1})}{1+r_t^b}} dH(a_{t-1})$, Since $x_t(a_{t-1}) = \alpha_N(1 - \alpha_N)^{\frac{1-\alpha_N}{\alpha_N}} [\frac{p_t^N a_{t-1}}{(\tilde{w}_t^N)^{1-\alpha_N}}]^{1/\alpha_N}$

$= \frac{\beta(1-\alpha_N)}{(1-\theta)\alpha_N \tilde{w}_t^N} \int_{a_{t-1}^*}^{\bar{a}} R_t(a_{t-1})v_{t-1}dH(a_{t-1})$, Since $R_t(a_{t-1}) = \frac{(1-\theta)x_t(a_{t-1})}{1-\frac{\theta x_t(a_{t-1})}{1+r_t^b}}$

$= \frac{\beta(1-\alpha_N)V_{t-1}}{(1-\theta)\alpha_N \tilde{w}_t^N} \underbrace{\int_{a_{t-1}^*}^{\bar{a}} R_t(a_{t-1})dH(a_{t-1})}_{=\frac{(1+r_t^d)(1-\theta)H(a_{t-1}^*)}{\theta(1-\phi)}}$, Since a_t is i.i.d

$= \frac{1-\alpha_N}{(1-\theta\phi)\alpha_N \tilde{w}_t^N} \underbrace{\beta(1 + r_t^d)V_{t-1}H(a_{t-1}^*)\frac{1 - \theta\phi}{\theta(1 - \phi)}}_{=V_t}$

$= \frac{1-\alpha_N}{(1-\theta\phi)\alpha_N \tilde{w}_t^N} V_t$

By equating the labor supply and labor demand in the non-tradable sector, with the law of motion of aggregate wealth, we can get the labor market clearing condition in the following equation:

$$\int_0^\infty z_N g_N(z_N) G_{T|N}(\frac{w_t^N}{w_t^T} z_N | z_N) dz_N = \frac{1-\alpha_N}{(1-\theta\phi)\alpha_N \tilde{w}_t^N} V_t \tag{29}$$

6. Proof of $\zeta < 0$

Theorem: If the following two conditions are satisfied:

1.the distributions of z_T and z_N are independent: $G(z_T, z_N) = G_T(z_T)G_N(z_N)$;

2.$\frac{g_x(z_x)z_x}{G_x(z_x)}$ (where $x = T, N$) are decreasing functions,

then $\zeta \leq 0$.

Proof: To prove $\zeta \leq 0$, we just have to prove $\frac{d\bar{z}_x}{dq_x} \leq 0$.

$$\frac{d\bar{z}_x}{dq_x} = \frac{1}{q_x}(\frac{dL_x/d\omega}{dq_x/d\omega} - \bar{z}_x) = \frac{1}{q_x}(\frac{dL_x}{dq_x} - \bar{z}_x) \tag{30}$$

where $\omega = \frac{w_x}{w_y}$. So $\zeta \leq 0$ really means that the marginal worker who enters the sector has a lower efficiency comparing to the sectoral average.

Now use the first equality in 31 and plug in the value defined in the beginning of this section:

$$\frac{d\bar{z}_x}{dq_x} = \frac{1}{q_x}(\frac{\int_0^\infty z_x^2 g_x(z_x)g_{y|x}(\omega z_x|z_x)dz_x}{\int_0^\infty z_x g_x(z_x)g_{y|x}(\omega z_x|z_x)dz_x} - \frac{\int_0^\infty z_x g_x(z_x)G_{y|x}(\omega z_x|z_x)dz_x}{\int_0^\infty g_x(z_x)G_{y|x}(\omega z_x|z_x)dz_x}) \tag{31}$$

$$= \frac{1}{q_x}(\mathbb{E}(a) - \mathbb{E}(b))$$

where $F_a(t) = \frac{\int_0^t \eta(\omega z_x)g_x(z_x)G_{y|x}(\omega z_x|z_x)dz_x}{\int_0^\infty \eta(\omega z_x)g_x(z_x)G_{y|x}(\omega z_x|z_x)dz_x}$, $\eta(\omega z_x) = \frac{wz_x g_{y|x}(\omega z_x|z_x)}{G_{y|x}(\omega z_x|z_x)}$,

and $F_b(t) = \frac{\int_0^t g_x(z_x)G_{y|x}(\omega z_x|z_x)dz_x}{\int_0^\infty g_x(z_x)G_{y|x}(\omega z_x|z_x)dz_x}$.

Now when z_T and z_N are independent, $\eta(z_x) = \frac{g_x(z_x)z_x}{G_x(z_x)}$.

Moreover, when it is a decreasing function, $F_a(t) \geq F_b(t)$, which gives the First

Stochastic Dominance. Thus $\mathbb{E}(a) \leq \mathbb{E}(b)$.

Therefore, $\zeta \leq 0$.

7. The Definition of Equilibrium

A set of variables: $\{a^*_{t-1}, r^d_t, r^b_t, p^N_t, p_t, w^N_t, \tilde{w}^N_t, w^T_t, \omega_t, V_t, L^T_t, L^N_t\}$ that satisfies the following equations ($p^T_t = 1$):

$$
\begin{aligned}
&w^T_t = (1-\alpha_T)(\alpha_T)^{\frac{\alpha_T}{1-\alpha_T}} A_{t-1}^{\frac{1}{1-\alpha_T}} (1+r^f_t)^{-\frac{\alpha_T}{1-\alpha_T}} \\
&w^N_t = \omega_t w^T_t \\
&\tilde{w}^N_t = w^N_t(1+\tfrac{\eta r^b_t}{1+r^b_t}) \\
&L^T_t = \textstyle\int_0^\infty z^T g_T(z^T) G_{N|T}(\tfrac{w^T_t}{w^N_t} z^T | z^T) dz^T \\
&L^N_t = \textstyle\int_0^\infty z^N g_N(z^N) G_{T|N}(\tfrac{w^N_t}{w^T_t} z^N | z^N) dz^N \\
&\tfrac{\tilde{w}^N_t L^N_t}{(1-\alpha_N)p^N_t} = (\tfrac{w^T_t L^T_t + w^N_t L^N_t}{p_t} + (1-\beta)\tfrac{V_t}{p_t})(\tfrac{p^N_t}{p_t(1-\gamma)})^{-\xi} \\
&p_t = [\gamma^\xi (p^T_t)^{1-\xi} + (1-\gamma)^\xi (p^N_t)^{1-\xi}]^{\frac{1}{1-\xi}} \\
&L^N_t = \tfrac{1-\alpha_N}{(1-\theta\phi)\alpha_N \tilde{w}^N_t} V_t \\
&\textstyle\int_{a^*_{t-1}}^{\bar{a}} R_t(a_{t-1}) dH(a_{t-1}) = \tfrac{(1+r^d_t)(1-\theta)H(a^*_{t-1})}{\theta(1-\phi)} \\
&V_t = \beta(1+r^d_t)V_{t-1}H(a^*_{t-1})\tfrac{1-\theta\phi}{\theta(1-\phi)} \\
&\tfrac{1}{1+r^b_t} = \tfrac{1-\phi}{1+r^d_t} + \tfrac{\phi}{1+r^f_t} \\
&R_t(a^*_{t-1}) = \tfrac{(1-\theta)x_t(a^*_{t-1})}{1-\frac{\theta x_t(a^*_{t-1})}{1+r^b_t}} = 1+r^d_t \Leftrightarrow p^N_t = \tfrac{(\tilde{w}^N_t)^{1-\alpha_N}}{a^*_{t-1}\alpha_N^{\alpha_N}(1-\alpha_N)^{(1-\alpha_N)}} (\tfrac{1}{\frac{1-\theta\phi}{1+r^d_t} + \frac{\theta}{1+r^f_t}})^{\alpha_N}
\end{aligned}
\tag{32}
$$